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DYNAMICS OF FARM PERFORMANCE AND POLICY IMPACTS: CASE STUDIES

OECD FOOD, AGRICULTURE AND FISHERIES
PAPER
JULY 2021 **n°165**

OECD
BETTER POLICIES FOR BETTER LIVES

OECD TRADE AND AGRICULTURE DIRECTORATE

Dynamics of Farm Performance and Policy Impacts: Case Studies

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This paper provides detailed farm level data evidence on the dynamics of farm performance from case studies covering crop farms in Australia, France, Italy and the United Kingdom (England and Wales), and dairy farms in the Czech Republic, Denmark and Norway, with different recent sample periods of five to thirty years. An increase in productivity over time is common to all countries and most crop farm classes, but productivity dynamics vary significantly. In Australia, strong productivity growth among the most productive crop farms has led to an increase in the gap between the highest and lowest performing farms; whereas in France, Italy and the United Kingdom, productivity growth was weak among the most productive crop farms and the lowest performing farms closed the productivity gap. Productivity also increased among dairy farms, with an increasing gap between the most and the least productive farm classes in the three sample countries. The impact of policy changes on performance dynamics is analysed for decoupled payments in France and England, and dairy payments in the Czech Republic. The main findings across countries and policy implications are discussed in *OECD Food, Agriculture and Fisheries Paper* N°164.

Key words: Agriculture, productivity, technical change, environmental sustainability, drivers of performance, farm structure, innovation, agricultural policy, decoupling

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

Acknowledgements

The authors are grateful to members of the OECD Farm-Level Analysis Network and country experts, who provided data and comments. This report also benefited from comments by OECD delegations to the Working Party on Agricultural Policies and Markets.

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Nine case studies have been undertaken to analyse the dynamics of farm productivity performance and policy impacts. Section 1 discusses the results of the farm performance dynamics for seven case studies. Additional information is presented in Annex B. The policy impact evaluation in Section 2 focuses on two cross-country case studies comparing policies across EU countries, including two different types of policy issues: the general policy design like the different CAP Pillar I decoupling implementation options in direct payments for arable farms in 2004, comparing France and the United Kingdom,[1] and a more specific dairy policy in the Czech Republic, using Estonia as comparison. Results on farm dynamics in Section 1 are relevant to cautiously interpret these policy impacts.

1. Dynamics of farm performance

Following the statistical techniques described in (OECD, 2020[2]), farms from a given country case study have been classified in two to four classes that are most homogenous among the members of each class, but most diverse between classes (Box 1). These classes are then ordered according to their relative productivity level. Switches from one class to another class with higher productivity are identified and analysed as productivity improving farms. Each case study is presented in a separated sub-section, each one discussing: first, the characteristics of the sector and its farm classes; second, the evolution of classes over time; third, the pattern of switches among classes; fourth, the drivers of productivity improvements; and finally a short summary of main findings in the case study.

Box 1. Measurement of productivity, definition of classes and construction of indexes

Farm-level productivity can be estimated in various ways. Due to constraints in data availability and estimation robustness we have adopted a production function based estimation approach. The statistical procedure used represent a variety of farm 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 e.g. (Sauer and Morrison Paul, 2013[6])). The first part of the econometric modelling exercise consists of choosing a technology function and a single-output based production function representation applying a second order approximation in the form of a flexible translog functional form was preferred. The productivity measure is then calculated as the estimated average output level per farm and year given employed inputs and stochastic influences.

The estimation of the production technology is combined with a probabilistic approach that allows considering simultaneously multiple characteristics of farms operating in a specific production system and robustly *identify various farm classes* along these characteristics, for which technologies are then estimated (see for example (Greene, 2002[7]; Greene, 2005[8]; Orea and Kumbhakar, 2004[9]; Sauer and Morrison Paul, 2013[6]). The application of latent class structures (LCM) results in a separation of the data into multiple technological classes. Each farm is then assigned to a specific class based on both the estimated technological (flexible TL function and the estimated probability relationships (Balcombe, Fraser and Kim, 2006[10]; Sauer and Morrison Paul, 2013[6]). Statistical tests are performed to choose the most adequate number of classes to be considered. 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.

Farms are production units, which differ along multiple characteristics and, hence, *multi-dimensional indexes* are defined and statistically estimated, to then be incorporated as elements of the class identification vector. 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. Accordingly, up to seven different farm indices are defined and estimated for

[1] The UK sample of matched farms included only farms in England.

each observation of the respective sample using the deviations of each index component from the sample mean. Z-score based deviations for these components, are used for the PCA. For subsequent analyses up to seven multi-dimensional indexes are chosen to identify and measure class membership per farm and year. The following indexes are retained: 1 Farm structure; 2 Environmental Sustainability; 3 Innovation-commercialisation; 4 Technology; 5 Diversity; 6 Individual; 7 Location; 8 Household; and 9 Financial. The detailed composition of these indexes is in Table 2.1 in OECD (2020[1]).

Source: Appendix A in OECD (2020[1]).

1.1. Australia: Crop farms 1989-2018

Australian broadacre crop farms have undergone significant structural change and modernisation over the past three decades, while facing some of the most difficult environmental conditions in recent history. Over the period of analysis (1989 to 2018), they have endured the millennium drought; a severe long-term drought throughout the 2000s which widely impacted Australian farmers. In addition, they have also been exposed to considerable structural adjustment spurred on by economic reform — namely deregulation and competition policy in the early 1990s. Australian crop farms are therefore an important focus of analysis in understanding both the impact of structural adjustment through economic reform and the challenges of the harsh Australian natural conditions on farm performance and dynamics.

Table B1 in Annex B provides a summary of the different crop farm classes estimated in (OECD, 2020[2]; OECD, 2020[3]) from most productive to least productive.

Class 2 most productive: These crop farms have lower levels of family labour and use above average fuel and chemicals per hectare, achieving a comparatively low score on the environmental sustainability index. Yet their innovation indicators are all above the mean, with these farms investing more, engaging in contract farming, and participating in land rental. Class 2 crop farms are capital intensive relative to their labour use, however, appear to retain scale efficiency due to their capital use per hectare being below the mean. The managers of these farms tend to be younger and more educated than their class 1 counterparts, and their location is concentrated in the wheat-sheep region, which is regarded as having favourable natural conditions for cropping. High performance crop farms derive lower off-farm income than average, tend to have higher assets, and receive lower levels of government support. Over the sample period from 1989 to 2018, approximately 87.6% of crop farms are estimated as belonging to the highest performance class (class 2). In the most recent sample year, 2018, 96.5% of crop farms were assigned to this high-performance class, implying that the Australian cropping sector is well optimised in terms of productivity and technical change. However, class 1 crop farms have below average sustainability according to the indicators used.

Class 1 least productive: These crop farms are more reliant on family labour and tend to be structured as sole traders or partnerships/trusts as well as being more environmentally sustainable due to their relatively leaner use of fuel and chemical inputs. Innovation index scores are lower due to a below average investment ratio and lower than average use of contract farming. Their capital to labour ratio is also lower, implying that class 1 crop farms are using technology less intensively. Their managers tend to be older and have achieved lower levels of formal education. The location of these farms tends to be in areas with less favourable natural conditions for broadacre cropping. These lower performance crop farms derive higher off-farm income, have lower than average assets and obtain higher levels of government support. Only 12.4% of crop farms belong to the low performance class over the sample period. In the most recent year, the class 1 membership falls to 3.5% of the sample. These farms are characterised as having low levels of productivity, technical change regress and above average land area.

Farm classes over time

The evolution of Australian crop farm classes in relation to productivity level, technical change and key performance indices is presented in Table 1.[2] Three time periods are selected for illustrative purposes relative to the sample start point (1989), middle (2003) and end (2018) to facilitate the observation of dynamic change over time for the respective classes. The share of high-performance crop farms progressed from 71.79% of the sample in 1989 to 75.51% in 2003, and then to 96.53% in 2018. The share of low performance crop farms experienced a corresponding decline over this period (28.21% in 1989; to 24.49% in 2003; to 3.46% in 2018).

Table 1. Australian crop farm classes – dynamics

First, mid and end year of period (1989, 2003, 2018)

	Performance class 2 Most productive (87.6% of crop farms)	Performance class 1 Least productive (12.4% of crop farms)
Number of farms		
1989	84	33
2003	259	84
2018	334	12
Performance		
Estimated values		
Productivity level (mean)		
1989	12.3685	11.9169
2003	13.0842	12.8280
2018	14.1740	12.7882
Technical change (% p.a.)		
1989	-1.06	-6.10
2003	0.10	-2.11
2018	1.35	-2.73
Characteristics		
Deviations from Standardised Sample Means[1]		
Farm structure (Index 1)[2]		
1989	0.7391	1.0470
2003	0.9688	0.7578
2018	2.0392	0.6132
Environmental sustainability (Index 2)		
1989	0.9442	0.5453
2003	1.2177	0.7875
2018	1.2680	1.3477
Innovation-commercialisation (Index 3)		
1989	0.6882	0.8789
2003	0.9944	0.9969
2018	1.7421	1.0818
Technology (Index 4)		
1989	2.0858	1.1883
2003	0.7468	1.1830
2018	0.9388	0.2591

[2] The reported numbers for the performance indicators are based on deviations from the standardised sample mean for each indicator and the specific choice of respective index components (as outlined in the report on phase I of this project (OECD, 2020[2]). The same methodology applies to similar tables in other country studies in this report.

	Performance class 2 Most productive (87.6% of crop farms)	Performance class 1 Least productive (12.4% of crop farms)
Diversity (Index 5) [3]		
1989	0.9660	0.8657
2003	1.0712	1.1570
2018	1.7669	1.7324

Notes: AWU: Annual Work Unit.
1. Deviations from sample means (=0), z-scores based, scaled values.
2. Interpretation of farm structure index scores: more positive value implies more family labour dependent and smaller operations.
3. Interpretation of diversity index scores: more positive value implies a more diverse production structure.
Source: Estimated and computed values (project phase I).

In terms of absolute productivity level, class 2 crop farms increased strongly over the three periods of observation by 6.5% from 1989 to 2003, and an additional 8.3% to 2018. By contrast, least productive class 1 farms experienced a decline of 1% in productivity from 2003 to 2018. Severe drought occurred throughout this period and the class 1 decline in productivity may reflect ineffective climate adaptation among many other possible factors. Technical change has increased over time for class 2 farms, yet has remained negative for class 1. Convergence in productivity and technical change between the two classes has been marginal or even negative.

Observing changes in the farm structure index over time, class 2 most productive crop farms experienced continuous increases and a substantial increase from 2003 to 2018, while class 1 crop farms experienced continuous decreases. More detailed analysis of the index components (not presented) indicates the farm structure decline experienced by class 1 farms relates to continuously decreasing family labour. For class 2 farms, the farm structure index increase can be explained by continuously increasing farm size (consistent with structural adjustment), increased hired wages expense, and a transition away from sole trader entity structures towards company structures.

Both class 1 and 2 crop farms appear to experience an increase in the environmental sustainability index for the periods of observation. Deeper analysis of the components used to construct this index indicates that the upward trend is driven by improved fuel efficiency reflecting improvements in machine efficiency.

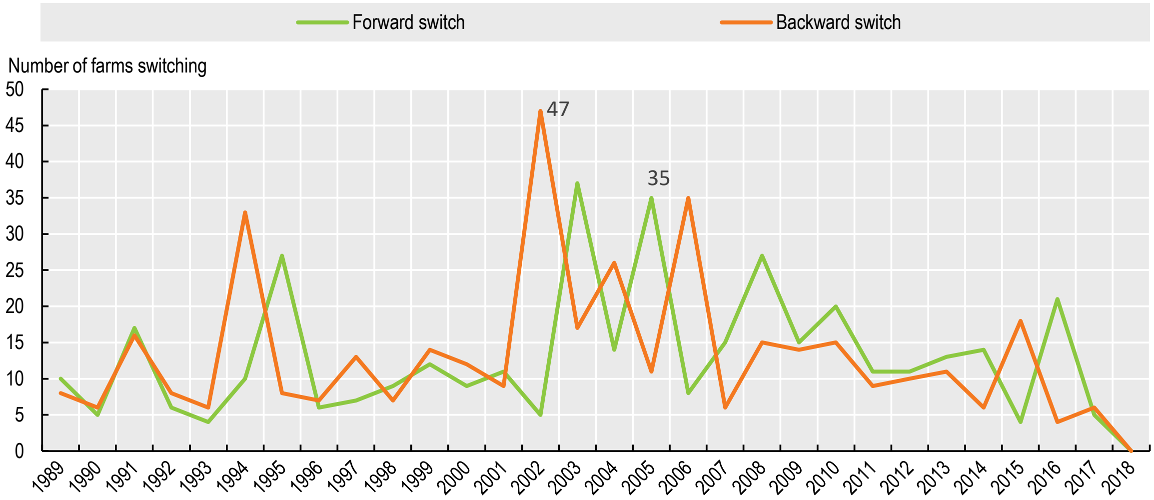
High performance crop farms in class 2 experienced a large jump in innovation, whereas this increase was more gradual for the least productive class 1 crop farms. The technology index is lower in 2018 than in 1989 for both classes which relates to decreasing depreciation over the period of analysis. Somewhat offsetting this decline is the increase in capital to labour ratio and use of materials per hectare. Production diversity has increased similarly for both classes over the three periods of observation.

Switching among farm classes

To better understand the dynamics of Australian crop farm performance, Figure 1 illustrates the number of sample farms that switched to either a more productive class ‘forward switch’, or a less productive class ‘backward switch’. The number of backward switching crop farms peaks in 2002, coinciding with harsh conditions during the Australian millennium drought. Switching volatility continues throughout this prolonged drought period, up until 2010 when the drought ended. While other factors are also likely to be at play, the dynamics are such that class switching may be temporary and partially driven by weather conditions.

Figure 1. Australian crop farms: Switching behaviour

Number of farms switching to higher or lower performing class per year



Class switching probabilities are summarised over the 1989 to 2018 period in Table 2. High performance crop farms have a high probability of remaining in their existing class (95%). By contrast, class 2 farms have a 65% probability of remaining in their class or a 35% chance of progressing into class 1.

Table 2. Australian crop farms: Inter-class switching dynamics

1989 to 2018

Probability of switching from t to t+1	Performance class 2 Most productive	Performance class 1 Least productive
Performance class 2 Most productive	0.95	**0.35**
Performance class 1 Least productive	0.05	0.65

Note: Bold – forward switchers.

The probability matrix in Table 2 represents the transition between different classes across the 1989 to 2018 period. This matrix of switching probabilities implies a dynamic process that can be represented by a Markov chain. Applying this chain analysis to the average shares of different classes across the whole period provides the results in Table 3. The dynamics in crop farm classes in Australia leads to almost hardly any change in the size of the most productive class 2 of juts 0.09%. This slow dynamic converges to stable shares relatively rapidly in seven periods. This implied dynamics contrast dramatically with the strong dynamics observed in the last three decades with observed increases in the share of the most performing class of 25 percentage points from 75% to 97%. Australian crop farms undertook a very significant structural adjustment process in the last few decades led by policy changes that deregulated the sector. However the current dynamics of farm classes seems to indicate that the scope for further structural change is small. Given the considerable structural adjustment that has occurred in the Australian cropping sector over the past few decades it is possible that these low performance crop farms in class 1 may represent the residual effect of historic policy settings prior to economic reform.

Table 3. Australian crop farms: Observed and implied dynamics of class shares

Shares applying Markov chain analysis

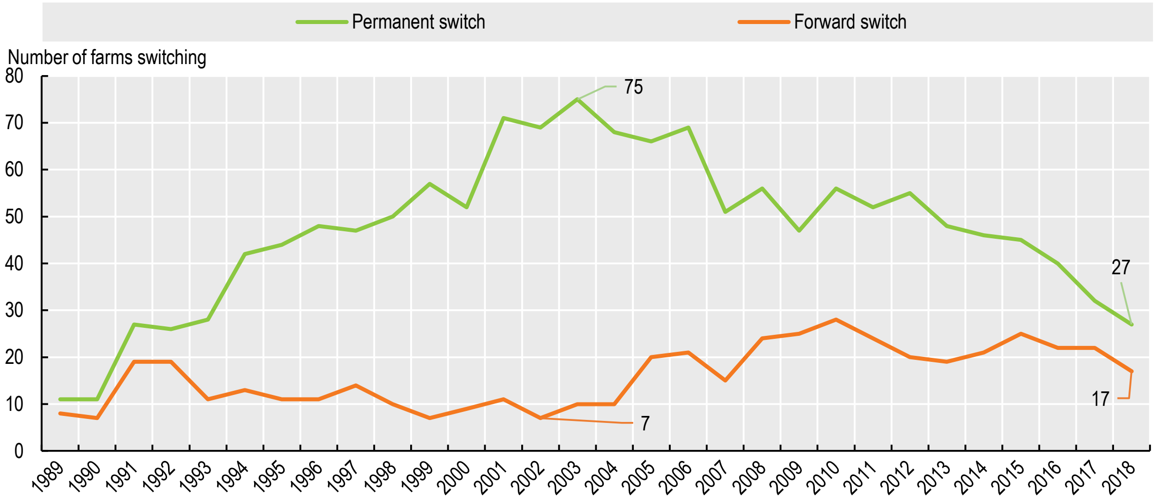
	Performance class 1 Most productive	Performance class 2 Least productive
Average 1989-2018	87.6%	12.4%
Observed changes in shares during the period	+24.7%	-24.7%
Implied shares In t+3	87.52%	12.48%
Implied shares In t+7 (convergence to steady state)	87.50%	12.50%

Notes: Markov analysis is applied to average shares in 1989-2018 with the probability transition matrix in Table 4. Technically, the implied shares at convergence represents the eigenvector of the matrix corresponding to Eigen value equal to 1.

Characteristics of productivity improvers

The dynamic movement of crop farms to more or less productive classes can be due to many factors including the temporary impact of natural conditions. For example, favourable rainfall may allow some class 1 farms to enjoy a brief period of high productivity; conversely, the opposite may occur during drought. It is therefore important to contrast or decompose ‘forward switchers’ into either permanent or occasional improvers — so that it is possible to differentiate between actual improvement in farm performance and temporary improvement driven by weather or other factors such as commodity price fluctuations. Figure 2 presents the number of permanent improvers and occasional improvers for the Australian crop sector each year. Permanent improvers are systematically more than occasional ones, indicating the structural nature of the transformation. The peak of permanent improvers was achieved in the early 2000s and has significantly declined in more recent years.

Figure 2. Australian crop farms: Permanent and occasional switchers



Notes: Permanent switcher: farms switching to a more productive class and remaining there or improving further.
Occasional switcher: farms switching to a more productive class but then fall back again to lower performing class.

The results in Table 4 identify possible drivers for forward and permanent switching probability. While both are important, policy makers are likely to value permanent improvements in farm performance ahead of potentially temporary forward switches — therefore coefficients for permanent improvers are the focus.

A reduction in family labour and hired labour is important to transitioning from class 1 to class 2, and possibly related to increased capital intensity. Increased use of fertiliser per hectare is highly significant and negative for both forward switching and permanent improving, indicating that a reduction in this intermediate input may improve farm performance (e.g. the use of precision agriculture for more efficient fertiliser use). Contract farming is highly significant, however may offer marginal benefits due to the small magnitude of the coefficient. Capital depreciation is highly significant, and an important driver based on the coefficient size.

Table 4. Australian crop farms: Drivers of occasional and permanent productivity improvement

Mixed-level multi-effects Probit models, 1989 to 2018

	Forward switchers	Permanent improvers
Farm structure (Index 1)		
Family weeks worked	-0.0036***	-0.0028**
Hired labour wages	-0.0001***	-0.0001**
Area operated	-0.0001	-0.0001
Entity	0.2047	0.090
Environmental sustainability (Index 2)		
Chemicals per hectare	-0.0047**	-0.0007
Fertiliser per hectare	-0.0072***	-0.0080***
Fuel per hectare	-0.0054*	-0.0038
Innovation-commercialisation (Index 3)		
Net capital investment	-0.0001**	-0.0001
Share of land rented	-0.7777**	0.0969
Contract farming	0.0001***	0.0001***
Technology (Index 4)		
Capital to labour ratio	-0.0013	-0.0023**
Labour per hectare	0.0006	0.0013**
Materials per hectare	0.0006	0.0001
Capital depreciation	5.2035*	7.8547***
Diversity (Index 5)		
Herfindahl Index (sqrt[Σ(yi/Y)2])	-0.0331	0.0817**
Individual (Index 6)		
Age (years)	0.0018	0.0005
Gender (1-female, 2-male)	0.0756	0.1509
Education	-0.1392***	0.0172
Region (Index 7)		
ABARES farming region (define)	-0.0006	-0.0007**
Household (Index 8)		
Off-farm income	0.0001	0.0001
Education spouse	-0.0463	-0.0746*
Age spouse	0.0004	0.0042
Gender spouse	0.0810	-0.1277
Financial		
Government assistance	0.0001	0.0001
Debt to equity ratio	0.0060	0.0012
Total assets	0.0001	0.0001***
Model quality		
Constant	-2.1246***	-2.3545***
Number of observations	8 921	8 921
LR chi2(31)	155.91	113.08
Prob > chi2	0.0000	0.0000
Pseudo R2	0.0488	0.0287
Log likelihood	-1517.9214	-1815.9301

Note: 1. standardised relative deviations from sample means; base outcome = 0; *significant at 10%, **significant at 5%, ***significant at 1%.
Source: Estimations.

Main findings from the Australian crop farms case study

Analysis of the Australian crop sector reflects an industry that is highly optimised overall with few low performers. Free market policy and among the lowest levels of producer support in the OECD are likely to be important, with policies that do not prop up low-performance farms. This policy approach seems to have effectively facilitated structural adjustment through resource reallocation also in some of the farms in the low productivity class 1 that have switched forward to class 2. The analysis reveals that sustainability components such as a more efficient application of fertilisers are important for improving the probability of crop farms switching to the high-performance class, a finding that could support policy making relating sustainability and productivity. Increased switching activity throughout the millennium drought period may also have important implications for policy makers, showing that extreme natural conditions may structurally change farm performance for the better, through resilient transformations. This link may be explored econometrically in future analysis. Policy makers may also observe the importance of farm structure and innovation characteristics which also appear to be important for class dynamics and improving performance.

1.2. France: Crop farms 1989-2016

The average crop output for French crop farm was about EUR 167 000 in 2016 (with a total output of about EUR 193 000). The variable cost significantly increased over the sample period 1989-2016. The average crop farm cultivated about 136 ha of land in 2016 (a significant increase considering the average area operated was about 77 ha in 1989). Table B2 in Annex B summarises the characteristics for the three different farm classes of French crop farms as estimated in (OECD, 2020[2]; OECD, 2020[3]). This includes productivity and technical change performance and characteristics defined by index 01 to 05. From more to less productive:

Class 4 most productive (11.6% of all farms). These are the economically most productive and environmentally most sustainable farms. They have larger farming operations and are more likely to be managed in partnerships as well as operated by older farmers that invest less than the average French crop farm but are more likely to have biofuel production. They also have the lowest propensity to technical change, which could be interpreted as farms that are already on the technical frontier.

Class 3 medium-high productive (55.4% of farms). Performance class 3 contains about 55% of all French crop farms that were considered in the analysis. These farms show a close to highest productivity and are above average environmental sustainable. These farms are larger operations (in terms of ha cultivated) and more likely to be partnerships. However, compared to the previous class these farms significantly invest in new technologies and produce with a higher capital intensity. These farms receive the highest subsidies compared to the peer group of French crop farms.

Class 2 medium-low productive (8.5% of farms). Crop farms with a lower productivity but still performing better than the average farm in the sample are part of performance class 2. These farms are least environmentally sustainable (given the indicators used in the previous analysis). These farms are mainly smaller operations, are most diversified and reliant on family labour. Operated mainly by younger farmers with a high capital intensity per hectare, these farms invest more than the average crop farm in France.

Class 1 least productive. Finally, performance class 1 farms are least productive with a lower than average environmental sustainability (based on the indicators used in the previous analysis). These least productive farms – about 25% of all farms – are smaller operations with lower investment and capital intensity compared to the average French crop farm. They are more likely to be located in remote areas and to rely on off-farm income.

Farm classes over time

Table 5 summarises the evolution of the four productivity performance classes over time (in 1989, 2002 and 2016) with respect to productivity level, technical change rate per year and core farm performance indicators. Overall, the share of more than average productive crop farms per year increased from 1989 to 2016. The number of farms in performance class 4 increased from about 4.3% to nearly 20% of all crop farms considered. The number of farms in performance class 3 increased from 54% to 73%.

Table 5. French crop farm classes - dynamics

First, mid and end year of period (1989, 2002, 2016)

	Performance class 4 Most productive (11.6%)	Performance class 3 Medium productive I (55.4%)	Performance class 2 Medium productive II (8.5%)	Performance class 1 Least productive (24.6%)
Number of farms				
1989	79	918	194	657
2002	224	1151	164	465
2016	325	887	134	305
Performance				
Estimated Values				
Productivity level				
1989	12.0516	11.7786	11.6106	10.9469
2002	12.0886	11.9207	12.0442	11.0304
2016	11.8479	11.9806	11.9232	10.9721
Technical change				
1989	-0.2623	-0.4702	0.6869	-5.0794
2002	-1.6381	1.2896	0.2633	-2.7663
2016	-3.8372	2.8165	2.5173	-1.0569
Characteristics				
Deviations from Standardised Sample Means[1]				
Farm structure[2]				
1989	-1.2674	0.0689	1.0484	0.8921
2002	-0.9374	-0.2525	0.4831	0.4369
2016	-0.2171	-0.2731	0.5861	0.3995
Environmental sustainability				
1989	0.0454	-0.0509	-0.1632	-0.1331
2002	0.0171	0.0544	-0.1996	-0.0109
2016	-0.0061	0.2569	-0.0589	0.0599
Innovation-commercialisation				
1989	0.7768	0.0899	-0.4536	-1.0956
2002	0.6651	0.3312	0.3059	-0.9327
2016	0.2666	0.3762	0.5414	-0.9436
Technology				
1989	-0.2928	-0.1118	1.3129	-0.1696
2002	-0.3244	-0.1293	1.7172	-0.2099
2016	-0.3214	-0.0722	2.0754	-0.2254
Diversity[3]				
1989	-0.0071	0.1104	1.3531	-0.2286
2002	-0.1629	-0.0239	1.0191	-0.2938
2016	-0.0773	-0.1319	0.7742	-0.3499

Notes: AWU: Annual Work Unit.
1. Deviations from sample means (=0), z-scores based, scaled values.
2. Interpretation of farm structure index scores: more positive value implies more family labour dependent and smaller operations
3. Interpretation of diversity index scores: more positive value implies a more diverse production structure
Source: Estimated and computed values (project phase I).

The level of productivity (as estimated in phase I of this project) increased for farms in medium performance classes 2 and 3 between 1989 and 2016 (Table 5). Most productive crop farms (performance class 4), however, fell back in terms of their absolute productivity level while the least productive farms in class 1 managed to keep their level of productivity. Over the total period considered a convergence is observed in productivity levels across all classes, not necessarily driven by productivity improvements, though.

With respect to the rate of technical change, between 1989 and 2016, most crop farms in France (those in medium productivity classes 2 and 3) succeeded in increasing their yearly technical change progress. However, the most productive farms in performance class 4 experienced a decline in their technical change. Over the total period considered, a significant divergence in yearly technical change rates across all classes is observed.

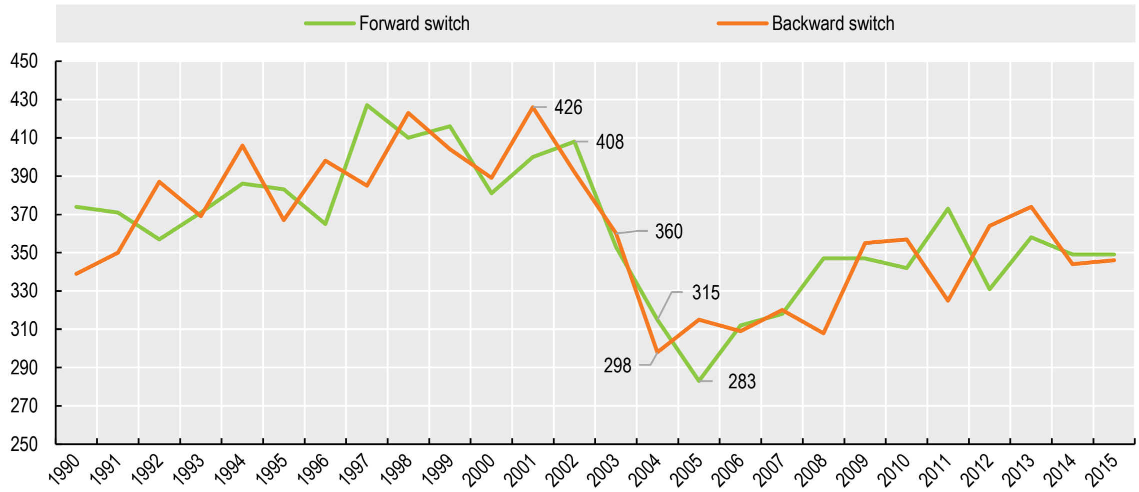
Less productive farms remain smaller operations and more family driven, but there is some convergence in farm structure related characteristics. Most crop farm classes increase their environmental sustainability in the time period considered, but not class 1 farms. Furthermore, the probability to innovate significantly increased for medium productive crop farm classes 2 and 3 from 1989 to 2016. Technology intensity and environmental sustainability have diverged across classes in the time period considered. Medium productive class 2 farms experienced an increase in the intensity of their crop production in the period considered. In terms of the diversity of production operations, a decrease in diversity is experienced by all farm classes. The difference between least and most diverse crop farm and least and most environmental sustainable crop farms have increased both by about 50% from 1989 to 2016.

Switching among farm classes

Figure 3 illustrates the evolution in the number of crop farms that switch to a more productive class – “forward switching farms” – and the development in the number of crop farms that switch to a less productive class – “backward switching farms” – from year to year. In general, a parallel movement of the number of farms switching back or forth per year is observed. A significant drop is found in the number of both forward or backward switching farms per year of more than 40% from 2001 to 2005. This observed drop in switching dynamics coincides with the CAP Fischler reform in 2003, aimed at decoupling support payments from agricultural output while introducing cross-compliance. This policy uncertainty might explain the generally lower level of structural change dynamics across French crop farm classes. In the subsequent years the number of forward or backward switching crop farms significantly increased but did not reach previous levels.

Figure 3. French crop farms: Switching behaviour

Number of farms switching to higher or lower performing class per year



Most forward switching farms switch by more than one class up from year to year. Most farms switch from performance class 1 to 3 (nearly 48% of all forward switching farms), from performance class 3 to 4 (more than 18%), and from performance class 2 to 3 (nearly 18%). In general, the share of forward switching farms is lower in higher performing classes, however, the shares of forward switchers increased over time throughout all classes. Table 6 summarises the various inter-class switching probabilities over the full period 1989 to 2016. The probability for a crop farm in performance class 2 to switch to performance class 3 is the highest overall farm switches considered (nearly 0.41), followed by the probability to switch from class 1 to class 3 (about 0.37). In terms of backward switching, the probability for a switch from performance class 4 back to performance class 3 is the highest with about 0.31.

Table 6. French crop farms: Inter-class switching dynamics, 1989-2016

Probability of switching from t to t+1	Performance class 4 Most productive	Performance class 3 Medium productive I	Performance class 2 Medium productive II	Performance class 1 Least productive
Performance class 4 Most productive	0.5432	**0.0641**	**0.0322**	**0.0602**
Performance class 3 Medium productive I	0.3127	0.7066	**0.4051**	**0.3749**
Performance class 2 Medium productive II	0.0238	0.0622	0.4081	**0.0524**
Performance class 1 Least productive	0.1203	0.1671	0.1546	0.5125

Note: Bold – forward switchers.

The shares of the most productive farm classes have increased significantly during the sample period 1989-2016, by 15 percentage points in the case the most productive class 4 (Table 7). The matrix of switching probabilities in Table 6 implies a dynamic process that can be represented by a Markov chain. Applying this chain analysis to the average shares of different classes across the whole period provides the additional results in Table 7. The observed change in the share of the most productive class 4 was large in the past, but dynamics in crop farm classes in France according to the estimated matrix of probabilities leads to modest expected further increases in the size of class 4, from 11.56% to 11.6%, revealing slow dynamics. Convergence to stable shares occurs relatively rapidly in 5 periods, with an improvement in the productivity profile of farm classes, but the change is extremely low at 0.04%, indicating that the system does not show the structural change dynamism of the past.

Table 7. French crop farms: Observed and implied dynamics of class shares

Shares applying Markov chain analysis

	Performance class 4 Most productive	Performance class 3 Medium productive	Performance class 2 Medium productive	Performance class 1 Least productive
Average shares 1989-2016	11.56%	55.38%	8.50%	24.56%
Observed changes in shares during the period	+15.41%	+4.05%	-2.38%	-17.08%
Implied shares In t+3	11.60%	55.40%	8.46%	24.54%
Implied shares In t+5 (convergence to steady state)	11.60%	55.40%	8.46%	24.54%

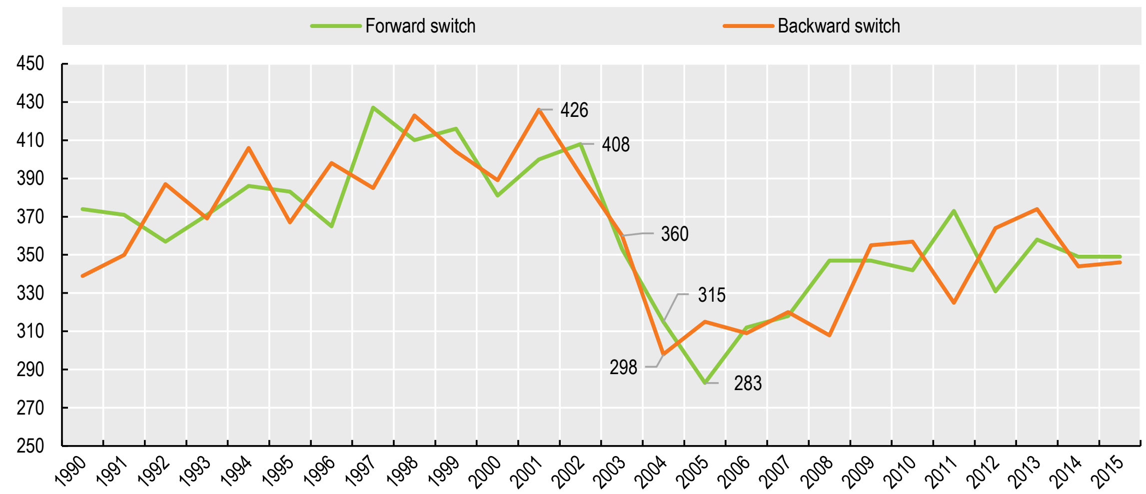
Note: Markov analysis is applied to average shares in 1989-2016 with the probability transition matrix in Table 8. Technically, the implied shares at convergence represents the eigenvector of the matrix corresponding to Eigen value equal to 1.

Characteristics of productivity improvers

Almost all forward switching crop farms show higher productivity level than non-switching farms. The rate of technical change is also more positive (or less negative) for most forward switching farms. The more productive the farms are the more pronounced the difference in technical change rates are between forward switching and non-switching crop farms. Most forward switching farms are comparably larger and less family labour dependent, and show a higher level of innovativeness but hardly differ on environmental sustainability. Finally, forward switchers are less input (technology) intensive than non-switchers.

The interest for policy making is not just on forward switching but on how to facilitate permanent improvements in farm performance. Out of all crop farms in the sample nearly 20% permanently improve their performance throughout the time period considered, and 40% improved only occasionally, i.e. after a forward switch they again fall back to a lower performing class. Figure 4 illustrates the development in the number of permanently improving versus occasionally improving crop farms in the time period considered. The number of permanently improving farms is systematically lower than occasionally improving farms in all years considered.

Figure 4. French crop farms: Permanent and occasional improvers



Notes: Permanent switch: farms switching to a more productive class and remaining there or improving further.
Occasional switch: farms switching to a more productive class but then fall back again to lower performing class.

Policy makers are interested in the main drivers of these permanent improvements on farm productivity classes. To infer statistically robust correlations between farm characteristics and different performance dimensions a multivariate regression analysis is conducted (Table 8). Most of the results for forward switchers are not statistically significant and therefore the discussion is focused on drivers for permanent improvers. The probability of permanently improving switches is significantly correlated with some indicators of farm structure, innovation, technology and individual/financial aspects (second column of Table 8).

In terms of farm structure, family ownership is a significant driver of permanent improvement, while for innovation and commercialisation, the drivers are net investment, the share of land rented, and the share of contract farming. Individual and financial assets are important for those permanently switching farms, in particular farmer’s experience and age, as well as off-farm income.

Table 8. French crop farms: Drivers of occasional and permanent productivity improvement

Bivariate Random Parameter Selection Models, 1989 to 2016

Outcome model	Forward switchers	Permanent improvers
01 Farm structure		
Family/hired labour ratio	0.0039	-0.0085
Family/hired labour ratio_one year lag	0.0105	0.0074
Land endowment (ha)	-0.0071	-0.0657
Land endowment (ha)_one year lag	-0.0255	-0.0768***
Form of ownership (1-family farms, 2-partnerships, 3-other)	-0.0093	-0.1179***
02 Environmental sustainability		
Chemicals use (EUR per ha)	-0.0042	-0.1111***
Chemicals use (EUR per ha)_one year lag	0.0164	0.0002
Organic production (1=yes, 0=no)	0.0043	-0.0109
Environmental subsidies per ha (EUR per ha)	-0.0054	-0.0344
Environmental subsidies per ha (EUR per ha)_one year lag	0.0022	0.0127
Tillage area (ha)	0.0264	-0.0032
03 Innovation-commercialisation		
Net investment ratio (per total assets)	0.0085	0.0626**
Net investment ratio (per total assets)_one year lag	0.0053	0.0501*
Share land rented	0.0176	0.0467***
Share land rented_one year lag	-0.0068	0.0483***
Biofuel income (EUR)	0.0098	-0.0304*
Miscellaneous income (EUR)	-0.0005	-0.0369*
Share contract farming	-0.0113	0.0087
Share contract farming_one year lag	0.0011	0.0644*
Insurance expenses (EUR)	-0.0266*	-0.0094
04 Technology		
Capital / labour ratio (EUR per AWU)	-0.0214	-0.0103
Capital / labour ratio (EUR per AWU)_one year lag	0.0003	-0.0047
Capital per ha (EUR per ha)	-0.0083	0.0387
Capital per ha (EUR per ha)_one year lag	-0.0018	-0.1008***
Labour per ha (AWU per ha)	0.0136	-0.0012
Labour per ha (AWU per ha)_one year lag	-0.0166	0.0864***
Materials per ha (EUR per ha)	-0.0012	0.0374
05 Diversity		
Herfindahl Index (sqrt[Σ(yi/Y)2])	0.0072	-0.0291
Herfindahl Index (sqrt[Σ(yi/Y)2])_one year lag	-0.0116	0.0045
Forest area (ha)	-0.0049	-0.0272
06 Individual		
Age (years)	-0.0007	0.0664***
07 Location (Index07)	0.0251**	0.0725***
08 Household		
Off-farm income share	-0.0033	0.0713***
Off-farm income share_one year lag	0.0037	0.0549***
Rural support (EUR)	0.0002	0.0074
09 Financial		
Total assets (EUR)	0.0359*	0.0631**
Total assets (EUR)_one year lag	-0.0056	0.0308
Total subsidies (EUR)	0.0077	0.0616***
Equity/debt ratio	0.3578	0.2296
Equity/debt ratio_one year lag	-0.0172	-0.7254

Note: 1. Standardised relative deviations from sample means; *significant at 10%, **significant at 5%, ***significant at 1%.
Source: Estimations.

Main findings from the French crop farms case study

The analysis of the dynamics of productivity classes of French crop farms shows an increase in the share of farms in high productivity classes during the sample period 1989-2016. The dynamics shows more occasional than permanent changes and leads to some convergence between farm classes with respect to productivity and technical change, without significant increases in productivity and a divergent evolution of sustainability performance. The number of class switches collapsed during the period of the 2003 CAP reform probably driven by policy uncertainty and policy decisions to keep coupling for about 25% of direct payments. The inherent dynamics in the switching probabilities show little scope for further productivity improvement in the current policy environment. The main drivers for permanent productivity improvers are structural factors such as family ownership and innovativeness as well as intensified commercial behaviour in terms of investment and renting land.

1.3. Italy: Crop farms 2008-2015

Italian agriculture is characterised by small-sized farms where more than 50% of the agricultural holdings have less than 5 ha with an average farm size of about 12 ha (EU28 average is about 16 ha). Farms are managed by relatively old farmers with only about 5% below 35 years of age. The average crop output per farm did not significantly increase over the period 2008-15. The average farm size in terms of land endowment did not change significantly and the variable input costs only slightly increased. The characteristics of the Italian crop farms in the different classes estimated in phase I of the project are comprehensively summarised by Table B3 (Annex B). From most productive, to least productive the following three classes have been identified:

Class 3 most productive (51.5% of all farms). Italian crop farms in performance class 3 are the most productive operations, but show a slightly negative annual technical change rate over the period investigated (2008 to 2015). These crop farms have the lowest share of family labour in the sample and operate with a higher than average farm size. Farms in performance class 3 are most probably non-single owners. They score slightly lower on environmental sustainability than the average crop farm in Italy. These farms show the highest share of rented land and a slightly higher net investment rate than the average crop farm. They are more likely to co-operate, have the highest share of irrigated land but are least likely to be engaged in agri-tourism. They have a high capital and material intensity, are most specialised and are least likely to diversify into non-agricultural, e.g. forestry, production, etc. The farm managers are younger and better educated than the average crop farmer in Italy, and off-farm income is of average importance.

Class 2 medium productive (41.5% of all crop farms). Class 2 farms are nearly half as productive as farms in performance class 3 and show a positive rate of technical change of about 1.5% per year. Family labour is important and typically a single person or family owns the farm. Farms in this class are slightly less endowed with land than the average crop farm in Italy, however, those farms operate with the highest environmental sustainability of all farms in the sample. They have a lower than average share of rented land and are least input intensive. Farms in class 2 have medium scores on diversification, their managers are older, and they are less likely to be located in less favoured areas and areas of high altitude.

Class 1 least productive (7%). This farms also have the lowest but a considerable positive technical change (of about 1.8% per year). They have the highest share of family labour across all crop farms but are also the smallest in terms of land size. Crop farms in this class have most likely a single owner and score lowest on environmental sustainability. Those farms show a high input intensity but are also most likely and significantly diversified in their production and have a high probability of being engaged in forestry production. The farm manager is slightly older than average and the farm is most likely located in less-favoured and high altitude areas of Italy.

Farm classes over time

Table 9 reports the dynamics in the development of the individual performance class with respect to productivity level, technical change rate per year and core farm performance indicators. The full sample period 2008 to 2015 is applied for the analysis, but the respective value for the years 2008, 2011 and 2015 is discussed below.

The overall share of more than average productive Italian crop farms per year slightly increased from 2008 to 2015. The number of farms in performance class 3 increased from 49% to about 52%, the number of farms in performance class 2 slightly decreased from about 42% to 41% of all crop farms considered. Performance class 1 with the least productive crop farms also slightly decreased in relative.

Table 9. Italian crop farms: Performance classes – dynamics

First, mid and end year of period (2008, 2011, 2015)

	Performance class 3 Most productive (phase I class 1, 51.5%)	Performance class 2 Medium productive (phase I class 3, 41.5%)	Performance class 1 Least productive (phase I class 2, 7%)
Number of farms			
2008	1 611	1 383	266
2011	1 419	944	159
2015	1 016	816	139
Performance			
Estimated values			
Productivity level			
2008	10.7528	10.1192	9.5582
2011	10.8122	10.1938	9.5391
2015	10.7322	10.2673	10.0453
Technical change			
2008	-0.0095	3.1120	4.3378
2011	-0.6448	1.5335	2.4365
2015	-1.3736	-0.4875	-1.2567
Characteristics			
Deviations from Standardised Sample Means[1]			
Farm structure[2]			
2008	-0.2791	0.1221	0.5326
2011	-0.1983	0.2249	0.3179
2015	-0.1318	0.2308	0.2383
Environmental sustainability			
2008	0.1333	0.0651	0.0678
2011	-0.0685	0.0328	-0.2692
2015	0.0083	0.0913	-0.5541
Innovation-commercialisation			
2008	0.1292	-0.1605	-0.5280
2011	0.2239	-0.2827	-0.6218
2015	0.3807	-0.2018	-0.6928
Technology			
2008	0.0308	-0.1383	-0.0634
2011	0.1840	-0.1927	0.1721
2015	0.0898	-0.1656	0.3056
Diversity[3]			
2008	-0.7666	0.7385	1.6515
2011	-0.7412	0.5474	1.3423
2015	-0.5901	0.7153	1.2206

Notes: AWU: Annual Work Unit.
1. Deviations from sample means (=0), z-scores based, scaled values.
2. Interpretation of farm structure index scores: more positive value implies more family labour dependent and smaller operations
3. Interpretation of diversity index scores: more positive value implies a more diverse production structure
Source: Estimated and computed values (project phase I).

The level of productivity slightly increased for farms in (medium) performance class 2 and (least) performance class 1 by about 1.4% and 5.1%, respectively. Most productive Italian crop farms (performance class 3), however, slightly fell back in terms of their absolute productivity level. Hence, over the total period considered a convergence in productivity levels is observed across all classes by about 45%, mainly driven by productivity improvements of the least productive crop farms.

However, all crop farm classes in Italy experienced a decrease in their technical change rate. Farms in performance class 3 show a decrease of about 1.4 percentage points over the full period 2008 to 2015, while farms in class 2 decreased about 3.6 percentage points and class 1 nearly 6 percentage points. Hence, crop farms in Italy converged with respect to the technical change rates towards negative technical change values in 2015.

There is significant convergence of structural characteristics (in terms of acreage, family/hired labour mix…) over all crop farm classes in Italy for the period 2008 to 2015. Least productive farms in class 1 significantly increased farm size and became less family labour dependent. Most productive crop farms in class 3 are less significantly larger than the average at the end of the period considered (2015).

Most and medium productive crop farms in Italy maintained or even increased their environmental sustainability between 2008 and 2015. But least productive crop farms experienced a significant decrease in environmental sustainability resulting in a significant divergence across farm classes. Such a diverging pattern is also found for the index innovativeness: most productive crop farms significantly increased their relative innovativeness (by nearly 3 times), whereas medium and least productive crop farms decreased their relative innovativeness (by about 1.3 times).

Most and least productive crop farms in Italy (performance classes 3 and 1) significantly increased the intensity of production in the period considered. Medium productive crop farms experienced a slight decrease, resulting in a significant divergence in technological intensity. Finally, in terms of diversification, least productive crop farms (class 1) became less diverse and most and medium productive crop farms (classes 2 and 3) increased or remained at their initial level of production diversity Overall, crop farms in Italy converged with respect to production diversity throughout the period.

In a nutshell, a significant convergence in farm structure related characteristics and the degree of diversification has occurred among Italian crop farms. However, differences in innovation-commercialisation related characteristics, technology intensity and environmental sustainability have diverged further across crop farm classes in the time period considered (2008 to 2015).

Switching among farm classes

Figure 5 illustrates the development in the number of Italian crop farms that switch to a more productive class – “forward switching farms” – and to a less productive class – “backward switching farms” – from year to year. In general, a decreasing trend is observed in the number of farms switching back or forth per year over the time period considered (2008 to 2015), indicating a slowing down of the process of structural change across farm classes. A significant increase is also found in forward switching dynamics in the years 2008/2009 (by about 40%) and, similarly, a significant increase in backward switching dynamics in the years 2011/2012 (by about 66%). From 2011 onwards, the number of backward switching crop farms in Italy matches or even exceeds the number of forward switching crop farms.

Most forward switching farms switch one class up from year to year, mainly from performance class 2 to 3 (more than 70% of all forward switching farms), but also from performance class 1 to 2 (more than 20%), and from performance class 1 to 3 (nearly 7%). The share of forward switching farms is higher in lower performing classes, and the shares of forward switchers increased over time throughout all classes.

Figure 5. Italian crop farms: Switching behaviour

Number of farms switching to higher or lower performing class per year

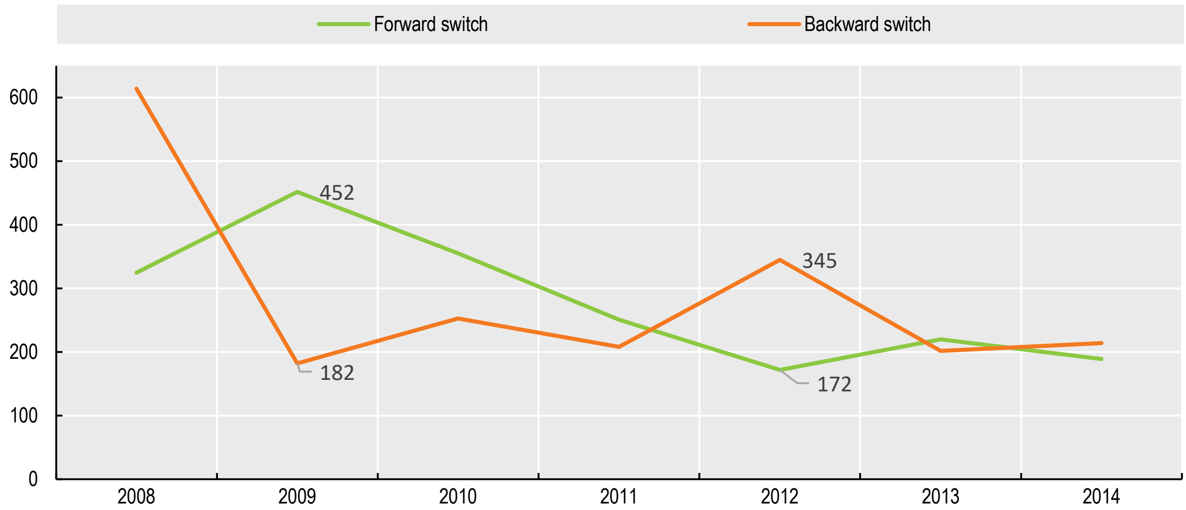


Table 10 summarises the various inter-class switching probabilities over the full period 2008 to 2015. The probability for a crop farm in performance class 1 to switch to performance class 2 is the highest over all farm switches considered (nearly 0.3). This is followed by the probability to switch from performance class 2 to class 3 (about 0.16) and from class 1 to 3 (about 0.09). In terms of backward switching, the probability for a switch from performance class 3 back to performance class 2 is the highest with 0.14.

Table 10. Italian crop farms: Inter-class switching dynamics

2008 – 2015

Probability of switching from t to t+1	Performance class 3 Most productive	Performance class 2 Medium productive	Performance class 1 Least productive
Performance class 3 Most productive	0.8507	**0.1625**	**0.0936**
Performance class 2 Medium productive	0.1352	0.7898	**0.2954**
Performance class 1 Least productive	0.0141	0.0477	0.611

Notes: Bold - forward switchers.

As a result of the inter-class dynamics the share of Italian crop farms is the most productive class 3 increased by 2.3 percentage points between 2008 and 2015, at the expense of classes 1 and 2. The matrix of probabilities in Table 10 represents the dynamics across farm classes and can be interpreted as a Markov transition matrix which implied dynamics are presented in Table 11. If the switching probabilities remained as observed during the sample period, Italian crop farms would hardly change their cross classes profile with less than 1 percentage point reduction in the share of farms in the most productive class 3. The convergence would be achieved in only five years, indicating that further structural change across farms is likely to be limited given the current environment and it could even imply a marginal relative growth of medium productive farms in class 2, rather than most productive farms in class 3.

Table 11. Italian crop farms: Observed and implied dynamics of class shares

Shares applying Markov chain analysis

	Performance class 3 Most productive	Performance class 2 Medium productive	Performance class 1 Least productive
Average shares 2008-2015	51.50%	41.50%	7.00%
Observed changes in shares during the period	+2.13%	-1.02%	-1.11%
Implied shares In t+3	50.88%	42.14%	6.99%
Implied shares In t+5 (convergence to steady state)	50.56%	42.40%	7.03%

Note: Markov analysis is applied to average shares in 2008- transition matrix in Table 12. Technically, the implied shares at convergence represents the eigenvector of the matrix corresponding 2015 with the probability to Eigen value equal to 1.

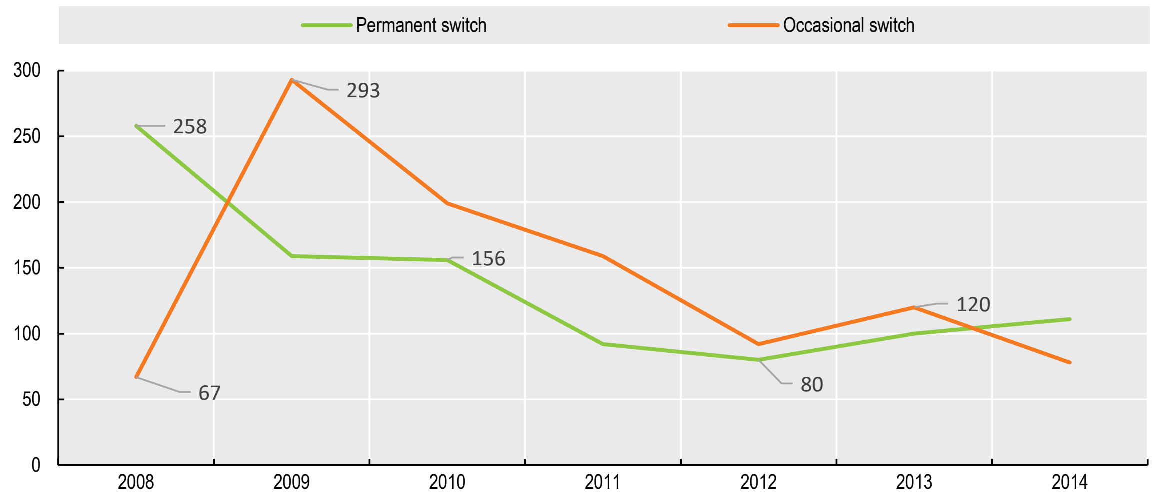
Characteristics of productivity improvers

Forward switching crop farms in Italy show a higher productivity level compared to non-switching crop farms with the difference increasing over the time period. The rate of technical change is, however, less positive for forward switching farms in most cases. The more productive the farms are the more pronounced the difference in technical change rates are between forward switching and non-switching crop farms. Most forward switching farms are comparably smaller and more family labour dependent. There is no clear pattern of forward switching farms with respect to environmental sustainability and input (technology) intensity (index 04). However, forward switching crop farms show a higher level of innovativeness compared to non-switching crop farms (index 03).

Policy interest is not only on forward switching crop farms and possible characteristics and factors for such a switching behaviour, but on crop farms that manage to permanently improve their performance and remain part of the higher performing class. Out of all Italian crop farms in the sample nearly 11% permanently improved their performance throughout the time period considered, about 12% only occasionally improved, i.e. after a forward switch to a higher performing class they again fall back to a lower performing class. Figure 6 illustrates the development in the number of permanent improving versus occasionally improving crop farms in the time period considered. The number of permanently improving farms is higher than occasionally improving farms in only two out of all seven years considered (i.e. in 2008/09 and 2014/15).

Figure 6. Italian crop farms: Permanent and occasional improvers

Number of farms switching permanently or occasionally to higher performing class per year



Notes: Permanent switch: farms switching to a more productive class and remaining there or improving further.
Occasional switch: farms switching to a more productive class but then fall back again to lower performing class.

To infer statistically robust correlations between productivity improving and crop farm characteristics and different performance dimensions a multivariate regression type analysis needs to be conducted. Both the probability of forward switching and of permanently improving farm performance are analysed. Table 12 reports the estimation results for two regression models using a bivariate random parameter selection estimator that accounts for likely sample selection bias and simultaneous decision making at farm level. Model I refers to forward switching farms whereas model II refers to permanently improving crop farms (i.e. permanent switchers) in Italy for the period 2008 to 2015. The estimates – especially those related to permanent switching behaviour – reveal statistically robust correlations for many of the farm characteristics and performance dimensions considered.

The estimation results in Table 12 suggest that the probability to permanently switch to a higher performance class is significantly correlated with characteristics related to farm structure, environmental sustainability, innovativeness, and production technology as well as intensity. Crop farms with a higher probability to permanently improve their performance are farms with less family labour dependence, less than average chemicals usage, and are more likely to produce organic. These farms show a higher share of rented land, a higher capital intensity, but also seem to be more diversified than their peer group. Non-permanent forward switcher farms tend to have weaker correlation and, sometimes, in the opposite direction (more chemical use and less diversification).

Table 12. Italian crop farms: Drivers of occasional and permanent productivity improvement

Bivariate random parameter selection models (2008 to 2015)

Outcome model	Forward switchers	Permanent switchers
Farm structure		
Family/hired labour ratio	0.0147	-0.1557***
Family/hired labour ratio_one year lag	0.0026	-0.0561
Land endowment (ha)	-0.1219**	0.0071
Land endowment (ha)_one year lag	-0.0065	-0.1019*
Form of ownership (1-family farms, 2-partnerships, 3-other)	-0.0505	0.0321
Environmental sustainability		
Chemicals use (EUR per ha)	0.2718***	-0.1457***
Chemicals use (EUR per ha)_one year lag	-0.1069**	0.0499
Organic production (1=yes, 0=no)	-0.1442***	0.0766**
Organic production (1=yes, 0=no)_one year lag	-0.0117	-0.0063
Environmental subsidies per ha (EUR per ha)	-0.0116	0.0067
Environmental subsidies per ha (EUR per ha)_one year lag	-0.0247	0.0015
Innovation-commercialisation		
Net investment ratio (per total assets)	-0.3218	-0.4068
Net investment ratio (per total assets)_one year lag	0.7144	1.4114
Share land rented	-0.0533	0.0915***
Share land rented_one year lag	-0.0049	-0.0039
Cooperation (probability)	-0.0024	-0.0504*
Cooperation (probability)_one year lag	0.0255	0.0192
Irrigated area ratio	-0.1232***	0.0159
Irrigated area ratio_one year lag	0.0596*	-0.0012
Agritourism (probability)	-0.0122	-0.0044
Agritourism (probability)_one year lag	-0.0173	0.0352
Technology		
Capital / labour ratio (EUR per hour)	-0.1419***	0.0902***
Capital / labour ratio (EUR per hour)_one year lag	0.1155***	-0.1237***
Capital per ha (EUR per ha)	0.0219	0.1824*

Outcome model	Forward switchers	Permanent switchers
Capital per ha (EUR per ha)_one year lag	-0.1238	0.0552
Materials per ha (hour per ha)	-0.0451	-0.2596***
Materials per ha (hour per ha)_one year lag	-0.0255	0.0917
Total assets (EUR)	0.3740	0.2481
Total assets (EUR)_one year lag	-0.7328	-1.2256
Diversity		
Herfindahl Index (sqrt[Σ(yi/Y)2])	-0.4265***	0.2288***
Herfindahl Index (sqrt[Σ(yi/Y)2])_one year lag	0.1016**	0.0154
Production diversity (yc/ΣY)	-0.4235***	0.1737***
Production diversity (yc/ΣY)_one year lag	0.1026**	-0.0905**
Forestry (probability)	-0.0097	-0.0585**
Forestry (probability)_one year lag	0.0039	0.0102
Individual		
Age (years)	0.0306	0.0291
Education (1:primary, 2: secondary, 3: high, 4: college 1st, 5: college 2nd)	-0.0632*	-0.0488**
Gender (1-male, 0-female)	-0.0326	0.0215
Location (index 07)	-0.1002***	0.0721***

Note: 1. Standardised relative deviations from sample means; *significant at 10%, **significant at 5%, ***significant at 1%.
Source: Estimations.

Main findings from the Italian crop farms case study

In the short period of seven years between 2008 and 2015, there has been a catching up process with respect to productivity growth for less productive farm classes 1 and 2, while the relative number of most productive farms increased by more than 2 percentage points. The implied dynamics in the switching probabilities during the period considered is unlikely to bring a further increase in the share of most productive farm class 3, which could even marginally decrease. The main drivers for permanent productivity improving farms are a low degree of family labour dependency, a less than average chemical usage, a higher share of rented land, a higher capital intensity and a higher level of diversification.

1.4. United Kingdom: Crop farms 1995-2017

The average crop output per farm across UK crop farms was about GBP 356 000 in 2017 (with a total output of about GBP 506 000). The variable cost items increased over time and the share of hired labour significantly increases for the average UK crop farm. The average farm operated about 283 ha in 2017 (an increase from an average of about 208 ha in 1995). Table B.4 in Annex B gives a comprehensive overview of the characteristics for the different farm classes estimated in (OECD, 2020[2]; OECD, 2020[3]). Descriptive statistics are reported for the essential class characteristics related to the various performance dimensions analysed: farm structure, environmental sustainability, innovation-commercialisation, technology, diversity, individual, location, household and financial. The estimated farm classes in the UK sample (including farms from England and Wales) are, from most productive least productive:

Class 3 most productive (49% of crop farms). Crop farms in this class are the most productive and achieve below average environmental sustainability. They are larger, more diversified operations, which invest in new technologies and activities. These farms are more capital intensive and achieve higher financial ratios. Their operators are more likely to be men, older than average and with better education level.

Class 2 medium productive (8% of crop farms). These crop farms are least environmentally sustainable and achieve close to highest productivity levels. They are smaller and more specialised operations than average and they use the most intensive farm practices. 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.

Class 1 least productive (43% of crop farms). Crop farms in performance class 3 are the most environmentally sustainable, using the most extensive farm practices, however, these farms are the least productive. They are smaller and more specialised than average. They are more likely to be operated by women, with lower education levels. They are less capital intensive than average, and have lower investment in new technologies.

Farm classes over time

Table 13 illustrates the dynamics in the development of the individual performance class with respect to productivity level, technical change rate per year and core farm performance indicators. The analysis covers the full time period 1995 to 2017. However, for illustration purposes the focus is on the first, mid and final year of this period 1995, 2008 and 2017. The distribution of farms across the three crop farm classes in the United Kingdom has dramatically changed over that period. The share of more than average productive crop farms in class 3 soared from 0.3% (in 1995) to about 91% (in 2017), whereas the number of farms in the least productive performance class 1 significantly decreased from about 98% in 1995 to only about 1% in 2017.

The level of productivity significantly increased for farms in medium performance class 2. However, most productive crop farms in class 3 fell back in terms of their absolute productivity level (from about 13.1 in 1995 to about 12.5 in the year 2017) as the class grew in size incorporating less productive farms. Least productive farms (performance class 1) also experienced a slight decline in their level of productivity (from about 11.8714 in 1995 to about 11.4108 in 2017) implying that the farms remaining in this class could not improve further in terms of the relative level of productivity. There was convergence between the two most productive classes that became the large majority of crop farms in the United Kingdom.

The rate of technical change increased only for the least productive crop farms in the United Kingdom over the time period considered, but the group became very small relative to other classes. Farms in the most productive performance class 3, however, experienced a significant drop in the technical change rate per year (to about -1.2% p.a. in 2017), once the class absorbed big numbers of less dynamic farms. Farms in the medium productive performance class 2 more or less stagnated in their positive technical change rate of about 2% p.a. in the year 2017. Overall, technical change rates between crop farms in the different performance classes seemed to diverge over the period considered.

Crop farms in the most productive performance class 3 are still the largest (based on hectares cultivated) among all farms in the sample at the end of the time period considered (year 2017). Crop farms in the least productive performance class 1 are still the smallest in terms of hectares cultivated but got less family labour reliant towards the end of the period considered. Medium productive crop farms managed to increase the area cultivated and to operate less family labour reliant over the period considered. Overall, crop farm structures across different performance classes in the United Kingdom have converged from 1995 to 2017 with a decrease in the difference between farm structure related maximum and minimum index.

With respect to environmental sustainability most productive crop farms in class 3 could improve based on the sustainability indicators used, in part as a consequence of incorporating previously least productive farms that were more sustainable. Also, least productive crop farms in class 1 significantly improved from 1995 to 2017, whereas medium productive crop farms significantly deteriorated in their environmental sustainability. Over the total time period considered the gap between the maximum and minimum environmental sustainability index score for crop farms in the United Kingdom increased.

Medium productive crop farms in the United Kingdom in class 2 significantly improved their innovativeness over the time period considered, whereas most productive crop farms in class 3 experienced a relative decline, however, still remain more than average innovative. Least productive crop farms in class 1 remain least innovative. The intensity of production significantly increased for least productive farms, remains highest for medium productive farms, and has been reduced for most productive farms in the period considered. Finally, least and medium productive farms increased the diversity of production structure in the period 1995 to 2017, whereas most productive farms experienced a relative decrease in their production diversity. Hence, the innovativeness, production intensity and diversity of production structure have converged between crop farms in different performance classes.

Table 13. UK crop farms classes – dynamics

First, mid and end year of period (1995, 2008, 2017)

	Performance class 3 Most productive (49.1%)	Performance class 2 Medium productive (8%)	Performance class 1 Least productive (42.9%)
Number of farms			
1995	2	45	700
2008	533	50	4
2017	469	40	6
Performance			
Estimated Values			
Productivity level (log)			
1995		11.8915	11.8714
2008	12.3394	12.2815	
2017	12.5531	13.1111	11.4108
Technical change (% p.a.)			
1995		2.0886	-8.7025
2008	1.8676	3.8549	
2017	-1.2212	2.0329	19.3311
Characteristics			
Deviations from Standardised Sample Means[1]			
Farm structure[2]			
1995		0.4458	0.1771
2008	-0.1311	0.3113	
2017	-0.1999	0.0814	0.3989
Environmental sustainability			
1995		-0.7898	0.5698
2008	0.0129	-0.9556	
2017	-0.1566	-2.6704	4.5218
Innovation-commercialisation			
1995		-0.2989	-0.4799
2008	0.2845	0.0805	
2017	0.5907	1.5363	-0.1496
Technology			
1995		3.5603	-0.1594
2008	-0.1769	1.0971	
2017	-0.0689	3.3691	0.9409
Diversity[3]			
1995		-0.9085	-0.7942
2008	0.6357	-0.0099	
2017	0.6632	0.1822	1.6385

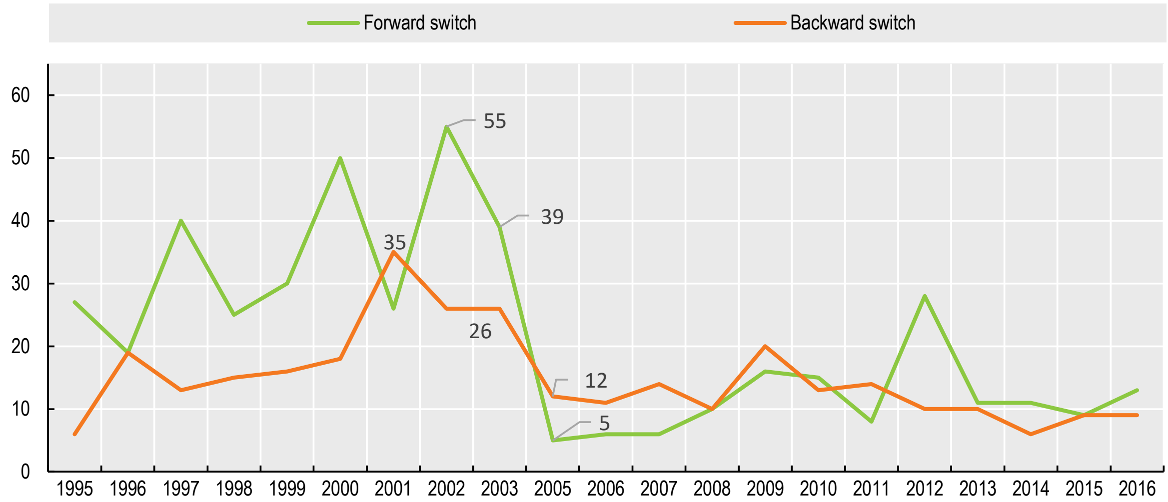
Notes: AWU: Annual Work Unit.
1. Deviations from sample means (=0), z-scores based, scaled values.
2. Interpretation of farm structure index scores: more positive value implies more family labour dependent and smaller operations.
3. Interpretation of diversity index scores: more positive value implies a more diverse production structure.
4. Indicators for Class 3 in 1995 and for Class 1 in 2008 are hidden to keep confidentiality with number of farms <5.
Source: Estimated and computed values (project phase I).

Switching among farm classes

Figure 7 illustrates the development in the number of crop farms that switch to a more productive class – “forward switching farms” – and the development in the number of crop farms that switch to a less productive class – “backward switching farms” – from year to year over the full time period 1995 to 2017. A lower level in the number of switches per year is observed from 2005/06 on, for both forward and backward switchers. In the majority of years more crop farms switch forward to a higher performing class than crop farms switch backward to a lower performing class (with the exception of the period from about 2005 to 2011).

Figure 7. UK crop farms: Switching behaviour

Number of farms switching to higher or lower performing class per year



Note: Year 2004 excluded (2004: 362 Forward switches, 2 Backward switches).

The number of forward switching farms per year significantly increased in the years 2002 to 2005 (e.g. from 55 to 362 in 2002/02 to 2004/05). This short-term spike in forward switching dynamics coincides with the CAP Fischler reform in the years around 2003. This policy reform allowed for decoupling support payments from specific agricultural output and introduced the concept of cross-compliance. Crop farmers in the United Kingdom may have adjusted to the option of the UK Government to decouple as much as possible, busting structural change and production efficiency through a more market oriented UK agricultural sector. Crop farms in the United Kingdom are used to price or demand side pressures and may be more effectively reacting to such factors to sustain farm profits compared to other EU crop farmers. In the subsequent years after 2004/05 the number of forward or backward switching crop farms increased again but at a lower level than before which might be due to efficiently reallocated production resources and productivity increases in the preceding years 2002-05. Figure 7 confirms that most of these forward switches were permanent and supported the long term structural change in the sector. After a few years of low levels of forward switching in 2005-07, the dynamics of forward switching started again at a slower pace from 2012 on.

The majority of forward switching crop farms switch by more than one class up from year to year, from class 1 to 3 (about 69% of all forward switching farms), and from performance class 2 to 3 (nearly 19%). Table 14 summarises the various inter-class switching probabilities over the full period 1995 to 2017. The probability for a crop farm in performance class 2 to switch to performance class 3 is the highest overall farm switches considered (nearly 0.13). This is followed by the probability to switch from performance class 1 to performance class 3 (about 0.09). This probability of 0.09 is enough to keep an intense forward switch dynamics because this changes are mostly permanent and once farms get into most productive class 3, the probability of moving backward is relatively very low at less than 0.02.

Table 14. UK crop farms: Inter-class switching dynamics

1995 – 2017

Probability of switching from t to t+1	Performance class 3 Most productive	Performance class 2 Medium productive	Performance class 1 Least productive
Performance class 3 Most productive	0.967-	**0.1352**	**0.0924**
Performance class 2 Medium productive	0.0188	0.851	**0.0156**
Performance class 1 Least productive	0.0142	0.0138	0.892

Notes: Bold – forward switchers.

The intensity of forward switches among UK crop farms is highlighted by the large increase in the share of high preforming class 3 from less than 1% in 1995 to 91% in 2017 and a similar decrease in the shares of the least productive class 1. The probabilities in Table 14 can be interpreted as the transition matrix of a Markov process. Table 15 summarises the implicit expected change in shares when applied to the average shares in the period. The average share of class 1 farms would increase by 9 percentage points from the average in the sample period of 49% to 58% in three years. But the overall scope of the adjustment in the long term is even larger, expected to increase to a steady state with 77% of crop farms being in the highest productivity class 3. Medium performance class 2 also grows, while the least performance class 1 collapses to only 11%.

Table 15. UK crop farms: Observed and implied dynamics of class shares

Shares applying Markov chain analysis

	Performance class 3 Medium productive	Performance class 2 Medium productive	Performance class 1 Least productive
Average shares 1995-2017	49.10%	8.00%	42.90%
Observed changes in shares during the period	+91%	+2%	-93%
Implied shares In t+3	58.19%	9.04%	32.77%
Implied shares In t+58 (convergence to steady state)	77.42%	10.98%	11.60%

Note: Markov analysis is applied to average shares in 1989-2016 with the probability transition matrix in Table 16. Technically, the implied shares at convergence represents the eigenvector of the matrix corresponding to Eigen value equal to 1.

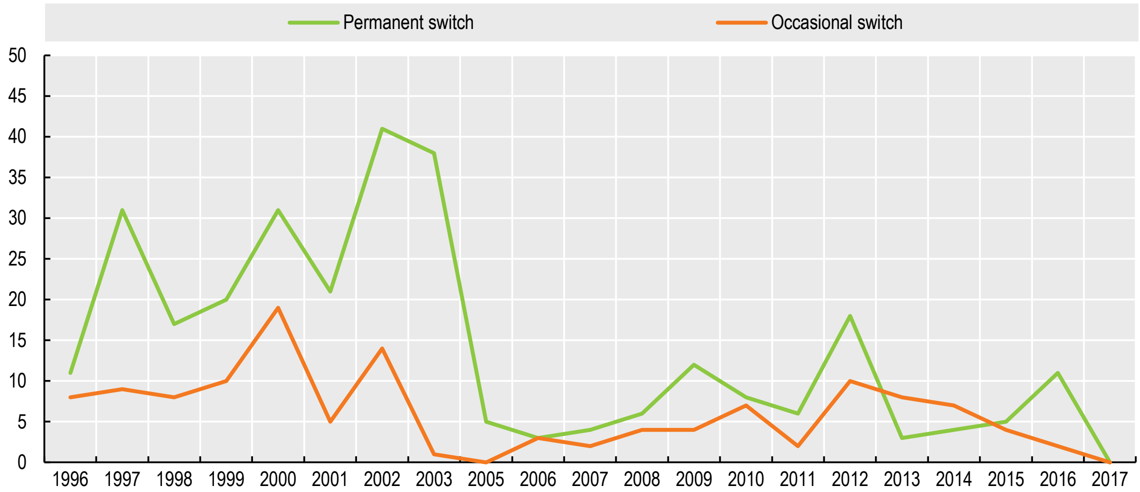
Characteristics of productivity improvers

Many forward switching crop farms in the United Kingdom show a higher productivity level compared to non-switching crop farms with the difference increasing over the time period considered. The rate of technical change is significantly more positive for these forward switching farms in all cases. The less productive the farms are, the more pronounced the differences in technical change rates are between forward switching and non-switching crop farms. Most forward switching farms are, however, a bit smaller in terms of acreage than the average non-switching farm and also a bit more family labour. The forward switchers are more environmental sustainable than non-switchers (index 02). However, the majority of forward switching crop farms show a higher level of innovativeness compared to non-switching crop farms (index 03). These differences in innovativeness are more significant for lower performance classes. Finally, forward switchers in higher performance classes (performance class 2) are less input (technology) intensive than non-switchers (index 04).

Out of all crop farms in the sample more than 23% permanently improve their performance throughout the time period considered, about 6% only occasionally improve, i.e. after a forward switch to a higher performing class they again fall back to a lower performing class (Figure 8). Permanent forward productivity switches radically dominate among UK crop farms, showing a very dynamic adjusting sector in a period of policy reform allowing farmers more freedom to choose what to produce.

Figure 8. UK crop farms: Permanent and occasional improvers

Number of farms switching permanently or occasionally to higher performing class per year



Notes: Permanent switch: farms switching to a more productive class and remaining there or improving further. Occasional switch: farms switching to a more productive class but then fall back again to lower performing class.

To identify possible drivers for forward and permanent switching behaviour based on statistically robust correlations between farm characteristics and different performance dimensions a multivariate regression type analysis has been conducted. Table 16 reports the estimation results using a multi-level mixed-effect probit estimator at farm level considering the most essential characteristics and drivers, and referring to forward switching farms and permanently improving farms (i.e. permanent switchers).

The regression based estimates reveal that forward switching and permanent switching behaviours among UK crop farms are more or less correlated with the same characteristics and drivers. For both switching types it is found that net investment (with a time lag of about one year) significantly increases the probability to switch forward to a higher productive class and also significantly increases the probability to switch permanently to a higher productive class. Less family labour dependency has a further positive and significant effect on the probability to switch forward and the probability to permanently switch for these crop farms. Individual characteristics – e.g. age and gender – also play a significant role for the probability to switch forward and also permanently increase the productivity. The results are less clear with respect to environmental sustainability related indicators. Finally, less capital intensive crop farms might have a slightly higher probability to permanently improve their productivity.

Table 16. UK crop farms: Drivers of occasional and permanent productivity improvement

Mixed-level multi-effects probit models, 1995 to 2017

	Forward switchers	Permanent improvers
Farm structure		
Family/hired labour ratio	-0.0795***	-0.0671*
Family/hired labour ratio_one year lag	-0.0096	-0.0072
Land endowment (ha)	-0.1386*	-0.0871
Land endowment (ha)_one year lag	0.0387	0.0375
Environmental sustainability		
Chemicals use (EUR per ha)	0.0079	-0.0162

	Forward Switchers	Permanent improvers
Chemicals use (EUR per ha)_one year lag	0.0761***	0.1007***
Environmental subsidies per ha (EUR per ha)	0.0625***	0.0467**
Environmental subsidies per ha (EUR per ha)_one year lag	-0.0025	-0.0549
Innovation-commercialisation		
Net investment ratio (per total assets)	0.0075	-0.0328
Net investment ratio (per total assets)_one year lag	0.0311**	0.0325**
Share land rented	-0.0066	-0.0061
Share land rented_one year lag	-0.0392	-0.0346
Technology		
Capital / labour ratio (EUR per AWU)	-0.0024	-0.0007
Capital / labour ratio (EUR per AWU)_one year lag	-0.0073	-0.0835*
Labour per ha (AWU per ha)	-0.0187	-0.0291
Labour per ha (AWU per ha)_one year lag	-0.0135	-0.0359
Diversity		
Herfindahl Index (sqrt[Σ(yi/Y)2])	-0.0242	-0.0185
Herfindahl Index (sqrt[Σ(yi/Y)2])_one year lag	-0.0423	-0.0441
Individual		
Age (years)	-0.1852**	-0.2573**
Gender (1-female, 2-male)	-0.2874**	-0.4289***
Education	-0.0221	-0.0032
(0 School only 1 GCSE or equivalent 2 A level or equivalent 3 College / National Diploma/ certificate 4 Degree 5 Postgraduate qualification 6 Apprenticeship 9 Other)		
Household		
Off-farm income share	0.0163	0.0273
Off-farm income share_one year lag	0.0063	-0.0431
Financial		
Total assets (EUR)	0.0842	0.0795
Total assets (EUR)_one year lag	-0.0483	-0.0589
Equity/debt ratio	0.0313	0.0162
Equity/debt ratio_one year lag	-0.0621**	-0.0482

Note: 1. Standardised relative deviations from sample means; *significant at 10%, **significant at 5%, ***significant at 1%.
Source: Estimations.

Main findings from the UK crop farms case study

UK crop farms experienced a very significant change in the profile of membership for different productivity classes during the sample period 1995-2017. Farms in the least productive class 1 massively moved forward directly to most productive class 3, or in two steps through medium productive class 2. These changes have been permanent in nature and remained at the end of the period. The productivity of the most productive class 1 was marginally reduced with the absorption of many previously less productive farms, while their environmental sustainability increased. The implied dynamics of farm classes in the crop sector in the United Kingdom show still potential for forward switches in a longer term adjustment period, as far as the current policy environment remains. Furthermore, the potential policy changes after Brexit could either reinforce this dynamics or hinder it. Several characteristics seem to drive the high probability of forward switching: net investment, less family labour dependency and higher chemical use. In terms of gender, farmers led by female farmers are more likely to permanently switch forward to more productive farm classes.

1.5. Czech Republic: Dairy farms 2005-2015

The analysis of dairy farms in the Czech Republic applies to a sample covering the period 2005 to 2015. The Czech dairy sector is highly consolidated having undergone a severe transformation process that followed the former planned economy approach by the Socialist regime. The number of dairy farms has declined by about 60% in the last 20 years with about 1 100 milk producing farms in 2016 delivering nearly 3 000 million litres of milk per year from more than 373 000 dairy cows (OECD, 2020[3]). The characteristics for three different farm classes estimated in phase I are summarised in Table B5 in Annex B

Class 3 most productive (33.9% of dairy farms). Dairy farms in performance class 3 are the most productive and exhibit the most significant positive technical change rate per year. They have a significantly lower than average share of family labour but a significantly larger herd and acreage and are most likely operated as co-operatives. Dairy farms in performance class 3 score lower than average on environmental sustainability indicators (such as stocking density, chemicals use per hectare and probability of producing organic) compared to the average Czech dairy farm. These farms show the highest scores on innovation and commercialisation and slightly lower than average capital per labour and average capital per cow intensity, while using slightly more than average labour per cow. These dairy farms are lower than average diversified, operate with a significantly higher assets' endowment and their managers are older than the average.

Class 2 of medium productive (32.5%). Those farms are significantly less productive than farms in class 3, and show a significantly lower technical change per year. Hired labour is important for those farms, which are smaller than the average dairy farm in the Czech Republic in terms of herd size with an about average land endowment. Dairy farms in class 2 are found to be more environmentally sustainable and have higher probability of producing organic. However, dairy farms in performance class 2 score slightly lower than average on innovation and commercialisation criteria such as net investment, share of land rented and biofuel income. Their capital intensity is the lowest of all dairy farms, and they employ the lowest rate of capital per cow. The specialisation of these dairy farms is the lowest of all Czech dairy farms and they are likely located in higher regions.

*Class 1 least productive (33.6%). T*he least productive farms in class 1 show a higher technical change rate per year than their colleagues in performance class 2. Family labour is most important for those dairy farms, which are considerably smaller than the average dairy farm in the Czech Republic in terms of herd size and land endowment. Dairy farms in class 1 are found to produce with a lower environmental sustainability performance measured by stocking density, chemicals use per hectare and probability of producing organic. Dairy farms in class 1 show the lowest investment level and significantly lower than average share of rented land. However, their capital intensity is higher than average whereas their assets endowment is significantly lower. Finally, farmers in this class 3 are the youngest and farms are less likely located in favourable areas.

Farm classes over time

Table 17 summarises the dynamics in the development of the individual performance class. The analysis covers the full time period from 2005 to 2015, but the table reports the respective value for the years 2005, 2010 and 2015. The share of more than average productive dairy farms per year increased in the Czech Republic from 2005 to 2015. The number of farms in the most productive performance class 3, however, decreased from about 38% (in 2005) to about 29% (in 2015), whereas the number of farms in the medium productive performance class 2 significantly increased from about 15% (in 2005) to about 49% (in 2015) of all dairy farms considered.

The level of productivity, as estimated in (OECD, 2020[2]), increased for all performance classes. Most productive dairy farms (performance class 3) experienced the highest (about 6.2%), least productive dairy farms the lowest increase in productivity (about 3.4%) over the full time period considered. The interclass difference in productivity levels, however, also increased. Hence, the productivity levels between Czech dairy farms in the different performance classes diverged (by about 3 percentage points) over the full period considered.

The rate of technical change significantly increased for all dairy farm related performance classes in the Czech Republic over the period 2005-2015: from about -3.2% p.a. to about 5.8% p.a. for class 1, from about -6.7% p.a. to about 5.9% for class 2, and from about -0.5% p.a. to about 4.5% for class 3). Farms in the medium productive performance class 2, however, experienced the most significant increase in the technical change rate per year (by about 12.6 percentage points over the full period considered). Overall, technical change rates between dairy farms in the different performance classes converged over the period.

Table 17. Czech dairy farms: Performance classes – dynamics

First, mid and end year of period (2005, 2010, 2015)

	Performance class 3 Most productive (33.9%)	Performance class 2 Medium productive (32.5%)	Performance class 1 Least productive (33.6%)
Number of farms			
2005	20	8	24
2010	34	33	39
2015	27	48	22
Performance			
Estimated values			
Productivity level (log)			
2005	16.2530	14.7666	14.0717
2010	16.6919	14.7125	14.1011
2015	17.2611	15.3247	14.5483
Technical change (% p.a.)			
2005	-0.5132	-6.6710	-3.1895
2010	1.3421	-8.2803	1.5692
2015	4.5233	5.9602	5.8021
Characteristics			
Deviations from Standardised Sample Means[1]			
Farm structure[2]			
2005	-1.0282	0.1278	1.4899
2010	-1.6003	0.3064	1.4597
2015	-2.2831	-0.0906	1.4419
Environmental sustainability			
2005	0.1221	0.3386	-0.7903
2010	0.2477	0.5152	-0.6895
2015	0.3042	0.1422	-0.6404
Innovation-commercialisation			
2005	-0.01858	-0.1239	-0.4407
2010	0.0959	-0.3401	-0.5019
2015	1.4347	-0.1109	-0.4887
Technology			
2005	-0.7166	-0.8272	-0.4441
2010	-0.1662	-0.3306	0.1031
2015	1.5195	0.3576	0.3135
Diversity[3]			
2005	-1.0279	0.7325	-1.9540
2010	0.0205	0.9214	-0.9774
2015	0.6986	1.2519	-0.7739

Notes: AWU: Annual Work Unit.
1. Deviations from sample means (=0), z-scores based, scaled values.
2. Interpretation of farm structure index scores: more positive value implies more family labour dependent and smaller operations.
3. Interpretation of diversity index scores: more positive value implies a more diverse production structure.
Source: Estimated and computed values (project phase I).

Czech dairy farms in the most productive performance class 3 are the largest (based on herd size) among all farms in the sample at the end of the time period considered and are least family labour dependent (year 2015). Dairy farms in the least productive performance class 1 are the smallest in terms of herd size but most family labour dependent throughout the full time period considered. The medium productive dairy farms in class 2 managed to significantly increase the herd size and to operate less family labour reliant over the period considered. Overall, dairy farm structures across different performance classes in the Czech Republic have diverged from 2005 to 2015.

Dairy farms in the most productive and medium productive classes 3 and 2 maintained or even significantly improved their environmental sustainability according to the sustainability indicators used. Also, least productive dairy farms in class 1 slightly improved their environmental performance from 2005 to 2015. Over the total time period considered, the environmental sustainability of dairy farms in the Czech Republic converged between the different performance classes by about 17%.

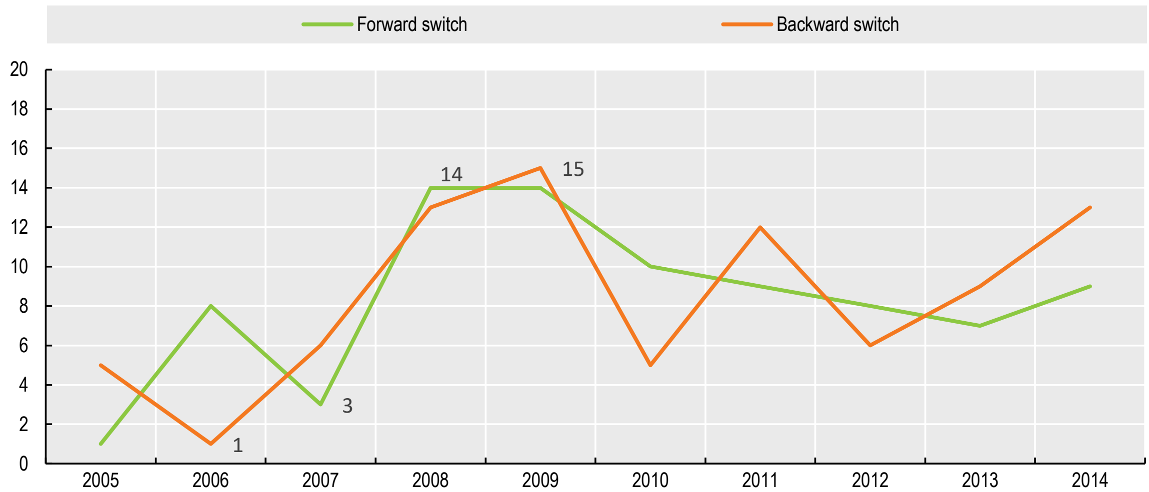
Furthermore, the empirical analysis reveals a divergence between performance classes with respect to innovativeness (index 03). Such a divergence is also confirmed for technology intensity, with a significant increase in the index gap. However, with respect to production diversity (index 05) Czech dairy farms experienced converging scores towards more diversification at the end of the period.

Switching among farm classes

Figure 9 illustrates the development in the number of Czech dairy farms that switch to a more productive class – “forward switching farms” – and the development in the number of dairy farms that switch to a less productive class – “backward switching farms” – from year to year. Over the time period considered (2005 to 2015) slightly more dairy farms switch backward (85 switches) than switch forward (83 switches). The number of forward switching farms per year increased until 2008/2009 from which on the number of forward switching dairy farms per year has been decreasing, with a peak of 14 forward switches in 2008/2009. Overall, the dynamics in the Czech dairy sector significantly slowed down between 2009 and 2012.

Figure 9. Czech dairy farms: Switching behaviour

Number of farms switching to higher or lower performing class per year



Forward switching dairy farms in the Czech Republic mostly switch by one class up from year to year. The majority of these forward switchers move from performance class 1 to 2 (about 51% of all forward switching farms), and from performance class 2 to 3 (about 42%). Table 18 summarises the various inter-class switching probabilities over the full period 2005 to 2015. The probability for a dairy farm in performance class 1 to switch to performance class 2 is the highest overall farm switches considered (about 0.12). This is followed by the probability to switch from performance class 2 to performance class 3 (about 0.11). In terms of backward switching, the probability for a switch from performance class 3 back to performance class 2 is the highest with nearly 0.14.

Table 18. Czech dairy farms: Inter-class switching dynamics

2005-2015

Probability of switching from t to t+1	Performance class 3 Most productive	Performance class 2 Medium productive	Performance class 1 Least productive
Performance class 3 Most productive	0.8513	**0.1067**	**0.0176**
Performance class 2 Medium productive	0.1370	0.7896	**0.1235**
Performance class 1 Least productive	0.0117	0.1037	0.8589

Notes: Bold – forward switchers.

The observed shares of the three productivity performance farm classes significantly changed over the sample period 2005-15. Both the most productive class 3 and the least productive class 1 reduced their relative size by 11 and 23 percentage points, respectively, while the medium productivity class 2 grows in relative size. When interpreting the matrix of probabilities in Table 19 as a Markov transition matrix and applying this concept to the average shares, a system of farm structures that converges toward the medium class 2 rather than the most productive class 3 results. However further reductions in the share of most productive farms are estimated to be small, of around 2 percentage points in three years, and less than 3 percentage points in the longer run.

Table 19. Czech dairy farms: Observed and implied dynamics of class shares

Shares applying Markov chain analysis

	Performance class 3 Medium productive	Performance class 2 Medium productive	Performance class 1 Least productive
Average shares 2005-2015	33.90%	32.50%	33.60%
Observed changes in shares during the period	-11%	+34%	-23%
Implied shares In t+3	31.85%	36.60%	31.55%
Implied shares In t+18 (convergence to steady state)	31.07%	38.24%	30.68%

Note: Markov analysis is applied to average shares in 2005-15 with the probability transition matrix in Table 20. Technically, the implied shares at convergence represents the eigenvector of the matrix corresponding to Eigen value equal to 1.

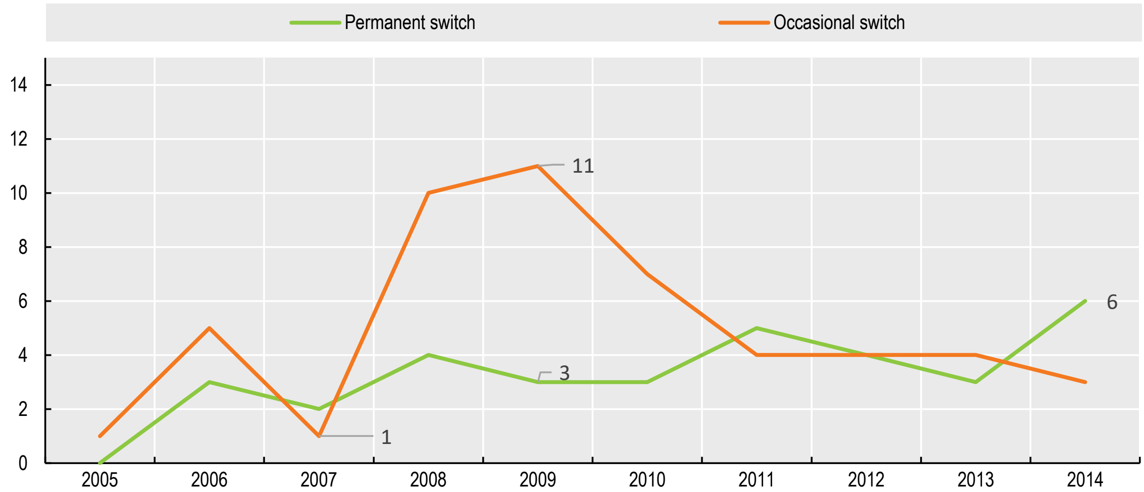
Characteristics of productivity improvers

All forward switching dairy farms in the Czech Republic show a higher productivity level compared to non-switching dairy farms with the difference significantly increasing over the time period considered. The rate of technical change is also higher for many of those forward switching farms. The less productive the farms are the less pronounced is the difference in productivity and technical change rates between forward switching and non-switching dairy farms.

Forward switching farms produce with a larger herd size and less family labour dependency compared to non-switching farms. Forward switchers in the Czech Republic are also more environmentally sustainable than non-switchers (index 02) and show a significantly higher level of innovativeness compared to non-switching dairy farms (index 03). Finally, forward switching dairy farms are less input (technology) intensive than non-switching dairy farms (index 04).

Out of all Czech dairy farms in the sample, about 12% permanently improve their performance throughout the time period considered, and about 24% occasionally improve, i.e. after a forward switch to a higher performing class these dairy farms again fall back to a lower performing class. Figure 10 illustrates the higher number of occasional improvers compared to permanent ones in most years considered (except the years 2007, 2011, 2012 and 2014). The trend in the number of permanently improving dairy farms steadily increased in the time period considered with the highest number of permanently forward switching dairy farms reaching six farms per year in the years 2014/2015. During the period 2007 and 2010, the number of occasionally improving dairy farms in the Czech Republic significantly increased (from 1 occasionally improving farm in 2007 to 11 in 2009) before then dropping back again to a lower level (i.e. around 4 occasionally improving farms per year).

Figure 10. Czech dairy farms: Permanent and occasional improvers



Notes: Permanent switch: farms switching to a more productive class and remaining there or improving further. Occasional switch: farms switching to a more productive class but then fall back again to lower performing class.

To identify possible drivers for forward and permanent switching behaviour based on statistically robust correlations between farm characteristics and different performance dimensions a multivariate regression type analysis has been conducted. Table 20 reports the estimation results for two regression models using a multi-level mixed-effect probit estimator at farm level considering the most essential characteristics and drivers, for both forward switching farms and permanently improving farms. The regression based analyses reveal that only a few characteristics are significantly correlated with the probability to permanently switching to more productive classes. This might be mainly due to relatively small sample size. Czech dairy farms with a lower stocking density and higher probability of producing organic show a positive correlation with the probability of permanently improving their performance. Furthermore, a higher amount of total assets and share of rented land seem positively correlated with the probability to permanently switch.

Table 20. Czech dairy farms: Drivers of occasional and permanent productivity improvement

Mixed-level multi-effects probit models (2005 to 2015)

	Forward switchers	Permanent switchers
Farm structure		
Family/hired labour ratio	0.0278	0.0257
Family/hired labour ratio_one year lag	0.0206	0.0071
Herd size (LU)	0.1668	0.3009
Herd size (LU)_one year lag	-0.4516	-0.6282
Land endowment (ha)	-0.7613**	-0.5862*
Land endowment (ha)_one year lag	0.6844	0.2894
Form of ownership	-0.1575	-0.3604
Form of ownership_one year lag	0.2095	0.0696
Environmental sustainability		
Stocking density (LU per ha)	-0.1237	-0.2351**
Stocking density (LU per ha)_one year lag	-0.0124	0.0884
Chemicals use (EUR per ha)	0.0707	-0.2257
Chemicals use (EUR per ha)_one year lag	-0.2963	-0.1124
Organic (probability)	-0.0734	-0.1281
Organic (probability)_one year lag	0.0991	0.1903**
Environmental subsidies per ha (EUR per ha)	-0.0401	-0.2574
Environmental subsidies per ha (EUR per ha)_one year lag	-0.0845	0.1830
Innovation-commercialisation		
Investment subsidies	0.0264	0.0363
Investment subsidies_one year lag	-0.0541	-0.0812
Net investment ratio (per total assets)	-0.2877**	-0.8035
Net investment ratio (per total assets)_one year lag	0.0062	-0.1385*
Share land rented	0.2180	0.3394**
Share land rented_one year lag	-0.2297	-0.2771*
Biofuel Income (EUR)	-0.0511	-0.0875
Biofuel Income (EUR)_one year lag	-0.1434	-0.0972***
Technology		
Capital / labour ratio (EUR per AWU)	0.1207***	0.0157
Capital / labour ratio (EUR per AWU)_one year lag	-0.0179	-0.1454
Capital per cow (EUR per LU)	-0.1576**	-0.0153
Capital per cow (EUR per LU)_one year lag	-0.1474	0.0338
Labour per ha (AWU per ha)	0.2335**	0.0969
Labour per ha (AWU per ha)_one year lag	-0.2122*	-0.3229**
Total assets (EUR)	0.5504	0.7516**
Total assets (EUR)_one year lag	-0.1596	0.2557
Diversity		
Herfindahl Index (sqrt[Σ(yi/Y)2])	-0.2718***	0.0603
Herfindahl Index (sqrt[Σ(yi/Y)2])_one year lag	-0.2864**	-0.1851
Individual		
Age (years)	0.1944	-0.0498
Age (years)_one year lag	0.1313	-0.0241
Location (index 07)	0.0579	0.1189

Note: 1. Standardised relative deviations from sample means; *significant at 10%, **significant at 5%, ***significant at 1%.
Source: Estimations.

Main findings from the Czech dairy farms case study

Dairy farms in the Czech Republic experienced significant changes in the period 2005-2015, consolidating a medium performing class of farms as the most numerous, while increases in productivity were spread across all classes. Environmental sustainability increased but at different pace across farm classes. Backward switches outnumbered forward switches, and occasional improvements were more frequent than permanent ones. The matrix of probabilities indicate that the dynamics of reduction in the relative size of the most productive class 3 is almost exhausted and could move only 2 or 3 percentage points out of that class. There are only a few characteristics that are significantly correlated with the probability to permanently switching to more productive classes, probably due to relatively small sample size. Those are lower stocking density, a higher amount of total assets and share of rented land.

1.6. Denmark: Dairy farms 2010-2016

Dairy production in Denmark is characterised by relatively large-scale production units with an average herd size of about 172 cows per farm and high milk yields per cow of about 9 500 kg/head in 2016. The total number of dairy farms has been steadily decreasing to about 3 300 dairy farms in 2016 and an average of about 1 600 tonnes of milk delivered per farm. The number of farms delivering more than 5 000 tonnes per farm and year has been significantly increasing over the last ten years. A comprehensive overview of the characteristics for the three different farm classes estimated in (OECD, 2020[2]) and reported in Table B6 in Annex B.

Class 3 most productive (66.9%). Dairy farms in most productive performance class 3 have positive technical change rate per year. They have the lowest share of family labour (i.e. a significantly lower family per hired labour share than the average farm in the sample) and a significantly above average herd and acreage size. These dairy farms score relatively low on environmental sustainability indicators (such as stocking density, chemicals use per ha and probability of producing organic). However, these farms show a slightly higher than average score on innovation and commercialisation with a higher than average rented land share and higher than average probability of being engaged in contracting. Performance class 3 farms show a slightly lower than average capital per labour intensity and capital per cow intensity than the average dairy farm in Denmark. They are less diversified than the average dairy farm, and their managers are slightly younger than the average Danish dairy farmer and generating lower than average off-farm income.

Class 2 medium productive (15.9%). Dairy farms in performance class 2 are (slightly) less productive than farms in class 3 but show a higher than average technical change per year. Hired labour is more important for those dairy farms, which are smaller than the average dairy farm in Denmark in terms of herd size but larger in terms of land endowment. Dairy farms in performance class 2 are found to be the most environmentally sustainable based on the various indicators used (such as stocking density, chemicals use per ha and probability of producing organic). Furthermore, these dairy farms invest significantly more than the average dairy farm in Denmark and their capital intensity is the highest of all dairy farms, employing most capital and fodder per cow. Medium productive dairy farms operate with innovative milking technologies, e.g. automatic milk systems or milking parlours. These dairy farms are diversified and their farm managers are of average age generating higher than the average off-farm income per farm.

Class 1 least productive (17.2%). Performance class 1 dairy farms are the least productive but show a significant technical change rate per year. Family labour is most important for those farms, which are considerably smaller than the average dairy farm in Denmark in terms of herd size and land endowment. These least productive dairy farms are found as environmentally sustainable as the average based on the various indicators used (such as stocking density, chemicals use per ha and probability of producing organic). Dairy farms in performance class 1 invest far less than the average dairy farm in Denmark and most likely operate with less innovative milking technologies as, for example pipeline systems or milking carousels. Their capital intensity is the lowest of all dairy farms and employ lowest levels of capital per cow. These dairy farms are the most diversified and their farm managers are of higher than average age generating the lowest off-farm income of the three classes and show the lowest level of assets endowment.

Farm classes over time

The dynamics in the development of the individual performance class with respect to productivity level, technical change rate per year and core farm performance indicators are summarised by Table 21. The analysis covers the full time period 2010 to 2016. However, for illustration purposes focus is on the first, mid and final year of this period, hence, the respective value for the years 2010, 2013 and 2016 are discussed below.

Table 21. Danish dairy farms classes: Dynamics

First, mid and end year of period (2010, 2013, 2016)

	Performance class 3 Most productive (66.9%)	Performance class 2 Medium productive (15.9%)	Performance class 1 Least productive (17.2%)
Number of farms			
2010	1403	353	1000
2013	1760	298	408
2016	1537	393	201
Performance			
Estimated values			
Productivity level (log)			
2010	15.3385	15.2829	14.8012
2013	15.4593	15.3993	14.8654
2016	15.6657	15.5965	14.8579
Technical change (% p.a.)			
2010	-1.8226	-4.8074	2.2252
2013	1.8212	6.6628	1.9655
2016	5.2992	16.7006	1.5351
Characteristics			
Deviations from Standardised Sample Means[1]			
Farm structure[2]			
2010	0.0755	0.2771	0.5806
2013	-0.1381	-0.0812	0.6239
2016	-0.4416	-0.2142	0.4398
Environmental sustainability			
2010	-0.1872	-0.1474	0.0378
2013	-0.2775	1.3103	0.1016
2016	-0.4482	1.9416	0.0797
Innovation-commercialisation			
2010	0.0583	-0.0167	-0.1479
2013	0.0907	0.1211	-0.4696
2016	0.0875	0.0465	-0.4466
Technology			
2010	-0.0007	0.6874	-0.1342
2013	-0.0309	0.3686	-0.3128
2016	-0.0871	0.4079	-0.2531
Diversity[3]			
2010	0.3086	1.7398	-2.3149
2013	0.0522	1.2651	-1.7846
2016	0.4529	1.0108	-2.1346

Notes: AWU: Annual Work Unit.
1. Deviations from sample means (=0), z-scores based, scaled values.
2. Interpretation of farm structure index scores: more positive value implies more family labour dependent and smaller operations.
3. Interpretation of diversity index scores: more positive value implies a more diverse production structure.
Source: Estimated and computed values (project phase I).

Over the period considered, the share of more than average productive dairy farms per year significantly increased from 2010 to 2016. The number of farms in the most productive performance class 3 significantly increased from about 51% (in 2010) to about 72% (in 2016), whereas the number of farms in the least productive performance class 1 significantly decreased from about 36% (in 2010) to only about 9% (in 2016) of all dairy farms considered.

The level of productivity slightly increased for all performance classes based on these yearly values (Table 21). Least productive dairy farms (performance class 1) experienced the lowest (about 0.4%), most productive dairy farms the highest increase in productivity (about 2.1%) over the time period considered. The interclass difference in productivity levels, however, increased and the productivity levels between dairy farms in the different performance classes slightly diverged over the period considered.

The rate of technical change significantly increased both for the most and medium productive dairy farms in Denmark over the time period considered (from about -1.8% p.a. in 2010 to about 5.3% p.a. in 2016, and from about -4.8% p.a. in 2010 to about 16.7% p.a. in 2017). Farms in the least productive performance class 1, however, experienced a significant drop in the technical change rate per year (to about 1.52% p.a. in 2016). Overall, technical change rates between dairy farms in the different performance classes also significantly diverged.

Dairy farms in the most productive performance class 3 are the largest (based on herd size) among all farms in the sample at the end of the time period considered and are least family labour dependent (year 2016). Dairy farms in the least productive performance class 1 are the smallest in terms of herd size but became less family labour dependent towards the end of the period considered. Medium productive dairy farms managed to increase the herd size and to operate less family labour reliant over the period considered. However, overall dairy farm structures across different performance classes in Denmark have diverged from 2010 to 2016.

Medium productive dairy farms (performance class 2) significantly improved their environmental sustainability. Also, least productive dairy farms (performance class 1) improved from 2010 to 2016, whereas most productive dairy farms significantly deteriorated in their environmental sustainability. Over the total time period considered the environmental sustainability of dairy farms in Denmark significantly diverged between the different performance classes.

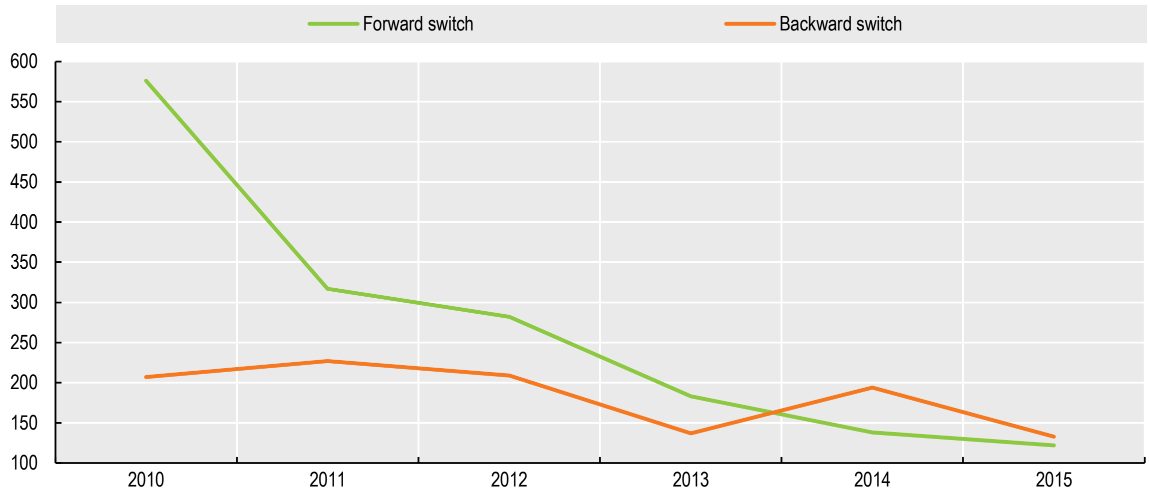
Furthermore, the empirical analysis reveals a divergence between performance classes with respect to the scores for the innovation index. Here, most and medium productive dairy farms increased their innovativeness from 2010 to 2016 whereas least productive dairy farms experienced a decrease. Regarding the technology intensity and diversity of production, however, a convergence in class levels is observed. All dairy farms experienced a decrease in technological intensity with a more pronounced change for farms in the most productive class 3. Finally, the diversity of production increased for most productive and least productive dairy farms but decreased for medium productive dairy farms in the period considered.

Switching among farm classes

Figure 11 illustrates the development in the number of dairy farms that switch to a more productive class – “forward switching farms” – and the development in the number of dairy farms that switch to a less productive class – “backward switching farms” – from year to year over the full time period 2010 to 2016. A significant decrease in the number of forward switching farms from year to year is observed, while the decrease in the number of backward switching dairy farms is less significant over the period considered. From 2014 on, the number of dairy farms switching backward to a less productive class is higher than the number of dairy farms switching forward to a more productive class.

Figure 11. Danish dairy farms: Switching behaviour

Number of farms switching to higher or lower performing class per year



Most forward switching dairy farms switch by more than one class up from year to year over the full time period investigated. The majority of these forward switchers move from performance class 1 to 3 (about 60% of all forward switching farms), and from performance class 2 to 3 (about 33%). Table 22 summarises the various inter-class switching probabilities over the full period 2010 to 2016. The probability for a dairy farm in performance class 1 to switch to performance class 3 is the highest overall farm switches considered (about 0.33). This is followed by the probability to switch from performance class 1 to performance class 2 (about 0.19). In terms of backward switching, the probability for a switch from performance class 3 back to performance class 2 is the highest with about 0.05.

Table 22. Danish dairy farms: Inter-class switching dynamics

2010 – 2016

Probability of switching from t to t+1	Performance class 3 Most productive	Performance class 2 Medium productive	Performance class 1 Least productive
Performance class 3 Most productive	0.9061	**0.1964**	**0.3329**
Performance class 2 Medium productive	0.0538	0.7927	**0.0366**
Performance class 1 Least productive	0.0401	0.0109	0.6305

Note: Bold – forward switchers.

The observed share of the most productive farm class 3 has increased by 21 percentage points between 2010 and 2016. The matrix of probabilities in Table 24 represents the dynamics of farm class membership that can be analysed as a Markov chain. When applying this method to the average shares over the period (66.9% for class 3), the implied dynamic increase in the share of the most productive farms leads to a share of 71.5% in three periods, with hardly any additional improvement in the longer term (Table 23). This is consistent with the strong forward dynamics at the beginning of the period 2010-2013, that was to some extent reversed in the last years of the period considered (Figure 11).

Table 23. Danish dairy farms: Observed and implied dynamics of class shares

Shares applying Markov chain analysis

	Performance class 3 Medium productive	Performance class 2 Medium productive	Performance class 1 Least productive
Average shares 2010-16	66.90%	15.90%	17.20%
Observed changes in shares during the period	+21%	+6%	-27%
Implied shares In t+3	71.48%	18.17%	10.35%
Implied shares In t+22 (convergence to steady state)	71.59%	20.05%	8.36%

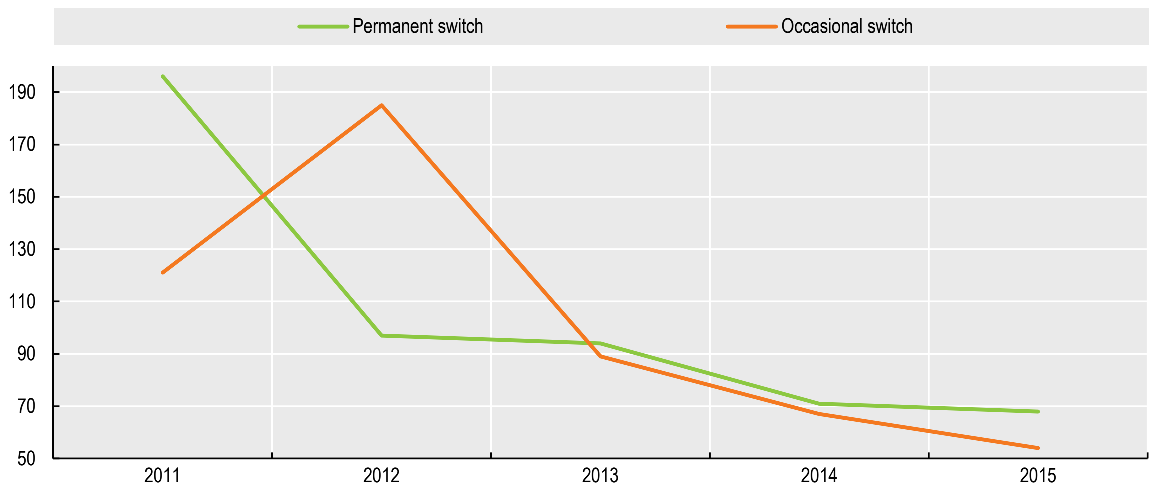
Note: Markov analysis is applied to average shares in 2010-16 with the probability transition matrix in Table 24. Technically, the implied shares at convergence represents the eigenvector of the matrix corresponding to Eigen value equal to 1.

Characteristics of productivity improvers

Many forward switching dairy farms in Denmark show a higher productivity level compared to non-switching dairy farms with the difference significantly increasing over the time period considered. The rate of technical change is significantly more positive for these forward switching farms in all cases at the end of the time period investigated. The less productive the farms are the more pronounced is the difference in technical change rates between forward switching and non-switching dairy farms. Forward switching farms produce with a larger herd size and are less family labour dependent compared to non-switching farms (index 01). Most forward switchers are, however, less environmentally sustainable than non-switchers (index 02). All forward switching dairy farms show a higher level of innovativeness compared to non-switching dairy farms (index 03) and these differences in innovativeness are more significant for lower performance classes. Finally, forward switchers in higher performance classes (performance class 2) are significantly more input (technology) intensive than non-switchers (index 04).

Out of all dairy farms in the sample more than 25% permanently improve their performance throughout the time period considered, about 17% only occasionally improve, i.e. after a forward switch to a higher performing class these dairy farms again fall back to a lower performing class (Figure 12). The interest of policy makers is not only on forward switching farms but also on farms that manage to permanently improve their performance and stay in the higher performing class or even improve further.

Figure 12. Danish dairy farms: Permanent and occasional improvers



Notes: Permanent switch: farms switching to a more productive class and remaining there or improving further.
Occasional switch: farms switching to a more productive class but then fall back again to lower performing class.

To identify possible drivers for forward and permanent switching behaviour based on statistically robust correlations between farm characteristics and different performance dimensions a multivariate regression type analysis has been conducted. Table 24 reports the estimation results referring to forward switching farms and to permanently improving farms. The correlations in the forward switcher group are hardly significant. The regression based analyses reveal that the probability of permanently switching to more productive classes is significantly correlated mainly with differences in farm structure, the level of innovativeness, and technology intensity. The Danish dairy farms in the sample are more likely to permanently improve their performance if they are more family labour dependent and produce with a smaller herd size. More innovative dairy farms (indicated by net investment, contract farming, as well as biofuel income) also significantly affect the permanent switching probability. Considering all technology intensity indicators it can be concluded that there is no clear evidence on the correlation with the probability to permanently switch. For example, a negative correlation is found with capital per labour and capital per cow, but also a positive correlation with fodder per cow and the more innovative milking system. Finally, more specialised dairy farms and more experienced farmers are more likely to permanently increase productivity.

Table 24. Danish dairy farms: Drivers of occasional and permanent productivity improvement

Bivariate random parameter selection models, 2010 to 2016

Outcome Model	Forward switchers	Permanent improvers
Farm structure		
Family/hired labour ratio	0.0999**	6.2113***
Family/hired labour ratio_one year lag	-0.0007	-5.0314**
Herd size (LU)	-0.1734	-6.8941***
Herd size (LU)_one year lag	-0.1058	0.2319
Land endowment (ha)	0.0356	12.7609***
Land endowment (ha)_one year lag	0.0308	0.9641**
Legal Form	-0.0091	3.4848**
Environmental sustainability		
Stocking density (LU per ha)	0.0055	-2.2493**
Stocking density (LU per ha)_one year lag	0.0019	0.4685
Chemicals use (EUR per ha)	0.0904	3.2467**
Chemicals use (EUR per ha)_one year lag	0.1691***	1.2153*
Organic (probability)	0.1102**	-9.1391***
Environmental subsidies per ha (EUR per ha)	0.0889*	-6.2219***
Innovation-commercialisation		
Net investment ratio (per total assets)	0.1475***	2.72859**
Net investment ratio (per total assets)_one year lag	-0.0041	2.2502**
Contract farming (probe)	-0.0054	2.7788***
Contract farming (prob)_one year lag	0.0019	1.1115
Share land rented	-0.0019	-2.4788**
Biofuel Income (Eur)	0.0331	2.1631**
Technology		
Capital / labour ratio (EUR per AWU)	-0.0282	-1.2506**
Capital / labour ratio (EUR per AWU)_one year lag	-0.0026	-0.1682
Capital per cow (EUR per LU)	0.2069	-6.8003**
Capital per cow (EUR per LU)_one year lag	0.0242	6.4401**
Fodder per cow (EUR per LU)	-0.1486	6.8011**
Fodder per cow (EUR per LU)_one year lag	0.1399	-7.2845**
Milking system (1-pipes, 2-carousel, 3-AMS, 4-milking parlour, 5-others)	0.0061	3.9927***
Milking system_one year lag	-0.0166	-2.845**

Outcome Model	Forward switchers	Permanent improvers
Breed type (breed: 1-RDM, 2-SDM, 3-Jersey, 4-Blandet)	-0.0168	0.3446*
Diversity		
Herfindahl Index (sqrt[Σ(yi/Y)2])	0.5203***	13.8470***
Individual		
Age (years)	-0.0191	1.6627**
Farming experience (years)	0.0202	-2.7615
Location		
Municipality (various)	-0.0462	2.2141**
Household		
Off-farm income share	-0.0355	-0.2646
Off-farm income share_one year lag	0.0542	-0.8722**
Financial		
Total assets (EUR)	0.0541	19.1911***
Total assets (EUR)_one year lag	0.0591	-4.8513**
Total subsidies (EUR)	-0.0089	-10.6063***
Equity/debt ratio	0.0482	0.1144
Equity/debt ratio_one year lag	-0.0033	2.4526*

Note: 1. Standardised relative deviations from sample means; *significant at 10%, **significant at 5%, ***significant at 1%.
Source: Estimations.

Main findings from the Danish dairy farms case study

The share of dairy farms in the most productive class 3 significantly increased in Denmark between 2010 and 2016. The level of productivity slightly increased for all performance classes but the difference between the most and least productive classes also increased. Technical change dropped in the least productive class, further diverging from the rest. Environmental sustainability deteriorated in the most productive class 3, while it improved in the medium class 2, leading to divergence between farm classes. Many dairy farms moved forward and permanently to more productive class 3, but most of the dynamics occurred in the first four years of the period considered, while they slowed down in the final two years. The implied dynamics would lead to few further improvements in the next few years and hardly any in the longer term. Danish dairy farms are more likely to permanently improve their performance if they are more family labour dependent, produce with a smaller herd size, are more innovative and more specialised.

1.7. Norway: Dairy farms 2005-2016

The analysis for a sample of dairy farms in Norway covers the period from 2005 to 2016. Agricultural production in Norway is characterised by its unique environmental and climatic conditions. The main agricultural income activities in Norway relate to dairy, crops and livestock production whereas the majority of farms is engaged in a mix of activities. About 60% of all farms are engaged in some kind of livestock production, about 35% in crop related activities and about 15% in dairy production. Thirty per cent of all farms active in milk production in 2017 have 30 or more cows, around 26% have 20-29 cows, and around 20% of these farms produce with a dairy herd size of about 15-19 cows.

Table B7 in Annex B summarises the characteristics for the three different farm classes as estimated in (OECD, 2020[3]). This includes productivity and technical change performance and characteristics defined by index 01 to 05. From more to less productive:

Class 3 most productive farms (64.6%) exhibit the most significant positive technical change rate per year. They have a relatively medium share of family labour and herd size, and a lower than average acreage size. Class 3 farms score slightly lower on environmental sustainability indicators (such as stocking density, chemicals use per hectare and probability of producing organic) compared to the average Norwegian dairy farm. Class 3 farms show a slightly lower than average capital per labour and capital per cow intensity, while using slightly more than average fodder per cow. These dairy farms are least diversified, their managers are younger than the average dairy farmer in Norway. Finally, dairy farms in performance class 3 generate only a low amount of off-farm income and operate with a medium assets' endowment.

Class 2 medium productive farms (19.2%) are almost as productive as in class 3, but with lower technical change per year. With larger than the average herd sizes and land endowment, hired labour is very important for those farms. Dairy farms in class 2 are found to be the most environmentally sustainable. However, class 2 farms score average on innovation and commercialisation. Their capital intensity is the highest of all dairy farms. The specialisation of these dairy farms is medium and their farm managers are slightly older than the average dairy farmer. Dairy farms in class 2 are likely located in advantageous regions for dairy production in Norway.

Class 1 least productive farms (16.2%) show negative technical change rate per year. Family labour is most important for those dairy farms, which are considerably smaller than the average dairy farm in Norway in terms of herd size and land endowment. These farms have an average environmental sustainability performance. Their capital intensity is the lowest of all dairy farms, they are highly diversified and farm managers are of average age. Dairy farms in class 1 are less likely located in favourable areas and operate with a lower than average assets endowment.

Farm classes over time

Table 25 summarises the evolution of the three productivity performance classes over time (in 2005, 2010 and 2016) with respect to productivity level, technical change rate per year and core farm performance indicators. The share of more than average productive dairy farms per year decreased in Norway from 2005 to 2016. The number of farms in the most productive performance class 3 decreased from about 73% (in 2005) to about 64% (in 2016), whereas the number of farms in the medium productive performance class 2 significantly increased from about 12% (in 2005) to about 22% (in 2016) of all dairy farms considered.

The level of productivity increased for all performance classes based on these yearly values (Table 25). The most productive dairy farms in class 3 experienced the highest increase (about 15%) over the full time period considered, while the medium productive farms in class 2 experienced the lowest, about 9%. The interclass difference in productivity levels, however, also increased from about 11.4% in 2005 to about 15.6% in 2016. Hence, the productivity levels between Norwegian dairy farms in the different performance classes diverged (by about 4 percentage points) over the full period considered.

The rate of technical change significantly increased for all dairy farm related performance classes in Norway from 2005 to 2016: from negative to positive in classes 1 and 2, and from about 2.1% p.a. to about 2.8% for class 3. Overall, technical change rates between dairy farms in the different performance classes converged over the period considered.

Dairy farms in the medium productive performance class 2 are the largest and least family labour dependent. The most productive dairy farms in class 3 managed to increase the herd size and to operate less family labour reliant over the period considered, converging to the levels of class 2. However, dairy farm structures have diverged across different classes, in particular the difference between the least productive class 1 and the rest.

Medium productive dairy farms in class 2 significantly improved their environmental sustainability. Least productive dairy farms in class 1 also improved their sustainability between 2005 and 2016, whereas most productive dairy farms in class 3 significantly deteriorated with respect to their environmental sustainability. Over the total time period the environmental sustainability of dairy farm classes in Norway diverged as indicated by higher differences between maximum and minimum index scores across classes in 2016.

In addition, the empirical analysis reveals a divergence between performance classes with respect to technology intensity (index 03). However, with respect to innovativeness (index 04) and production diversity (index 05) Norwegian dairy farms experienced converging scores between 2005 and 2016. All dairy farm classes succeeded in improving their innovativeness.

Table 25. Norwegian dairy farms: Performance classes – dynamics

First, mid and end year of period (2005, 2010, 2016)

	Performance class 3 Most productive (64.6%)	Performance class 2 Medium productive (19.2%)	Performance class 1 Least productive (16.2%)
Number of farms			
2005	378	61	76
2010	285	113	75
2016	290	100	63
Performance			
Estimated values			
Productivity level			
2005	6.1503	6.2285	5.5922
2010	6.7139	6.7587	6.0091
2016	7.0789	6.7809	6.1237
Technical change			
2005	2.0139	-0.9242	-1.8309
2010	2.7153	0.2465	-0.8668
2016	2.7721	1.7962	1.1439
Characteristics			
Deviations from Standardised Sample Means[1]			
01 Farm structure[2]			
2005	0.6257	0.1702	0.6597
2010	-0.1610	-0.8039	0.1433
2016	-0.4683	-0.7712	0.0685
02 Environmental sustainability			
2005	-0.2264	0.5306	0.2689
2010	-0.2427	1.0035	0.5085
2016	-0.5618	1.0656	0.3038
03 Innovation-commercialisation			
2005	-0.3120	-0.3351	0.0157
2010	-0.1233	-0.0951	0.0832
2016	0.2600	0.2661	0.5155
04 Technology			
2005	-0.7632	-0.4473	-0.6771
2010	-0.0719	0.2344	-0.1192
2016	0.9073	0.5936	0.4651
05 Diversity[3]			
2005	-0.3543	0.1013	1.9074
2010	-0.4541	-0.1481	1.7358
2016	-0.5856	-0.0475	1.4639

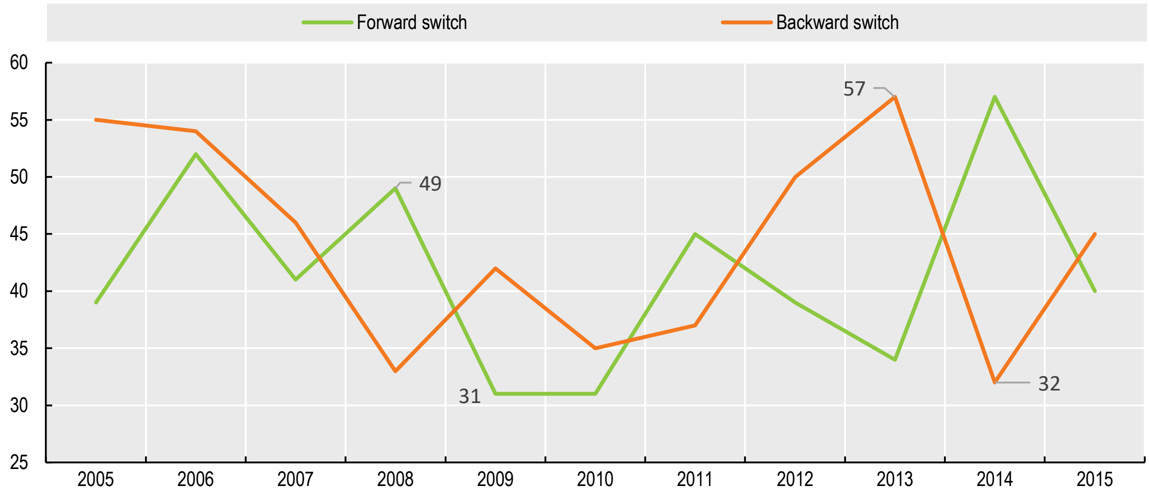
Notes: AWU: Annual Work Unit. 1. Deviations from sample means (=0), z-scores based, scaled values. 2. Interpretation of farm structure index scores: more positive value implies more family labour dependent and smaller operations. 3. Interpretation of diversity index scores: more positive value implies a more diverse production structure. Source: Estimated and computed values (project phase I).

Switching among farm classes

The dynamic of farm performance over time is to a great extent reflected by the number of switches between farm classes. Some farms switch to a more productive class – "forward switching farms" – while others to a less productive class – "backward switching farms". Between 2005 and 2016, more dairy farms switched backward (486) than switched forward (458) (Figure 13). Furthermore, a decrease is observed in the number of forward switching farms per year until 2009/2010, and then an increase with a peak of 57 forward switches in 2014/2015. The number of backward switching dairy farms followed a similar pattern with about one year of advance.

Figure 13. Norwegian dairy farms: Switching behaviour

Number of farms switching to higher or lower performing class per year



Most forward switching dairy farms in Norway switch by only one class up. The majority of these forward switchers move from performance class 2 to 3 (about 49% of all forward switching farms), and from performance class 1 to 3 (about 30%). Table 26 summarises the various inter-class switching probabilities over the full period 2005 to 2016. Most classes have the highest probability of remaining in the same class (0.88 in class 3, 0.71 in class 2 and 0.74 in class 3). The probability for a dairy farm in performance class 2 to forward switch to class 3 is the highest (0.21) and well above the probability of switching backwards to class 1 (0.07).

Table 26. Norwegian dairy farms: Inter-class switching dynamics

Average probabilities, 2005-2016

Probability of switching from t to t+1	Performance class 3 Most productive	Performance class 2 Medium productive	Performance class 1 Least productive
Performance class 3 Most productive	0.8875	**0.2105**	**0.1529**
Performance class 2 Medium productive	0.0684	0.7115	**0.1064**
Performance class 1 Least productive	0.0441	0.0780	0.7407

Notes: Bold – forward switchers.

The matrix of switching probabilities in Table 26 implies a dynamic process that can be represented as a Markov chain. Applying this chain analysis to the average shares of different classes across the whole period provides the results in Table 27. The dynamics in dairy farm classes in Norway leads to reductions in the size of the most productive class 3 from 65% to 63% in three periods and 62% in the longer run. The least productive class 1 increases its share from 16% to 17%. This implied dynamics confirms the observed reduction in the share of farms in the most productive class 3 by 9 percentage points.

Table 27. Norwegian dairy farms: Observed and implied dynamics of class shares

Shares applying Markov chain analysis

	Performance class 3 Most productive	Performance class 2 Medium productive	Performance class 1 Least productive
Average shares 2005-16	64.60%	19.20%	16.20%
Observed changes in shares during the period	-9.38%	10.23%	-0.85%
Implied shares In t+3	62.98%	20.45%	16.57%
Implied shares In t+18 (convergence to steady state)	62.16%	20.96%	16.88%

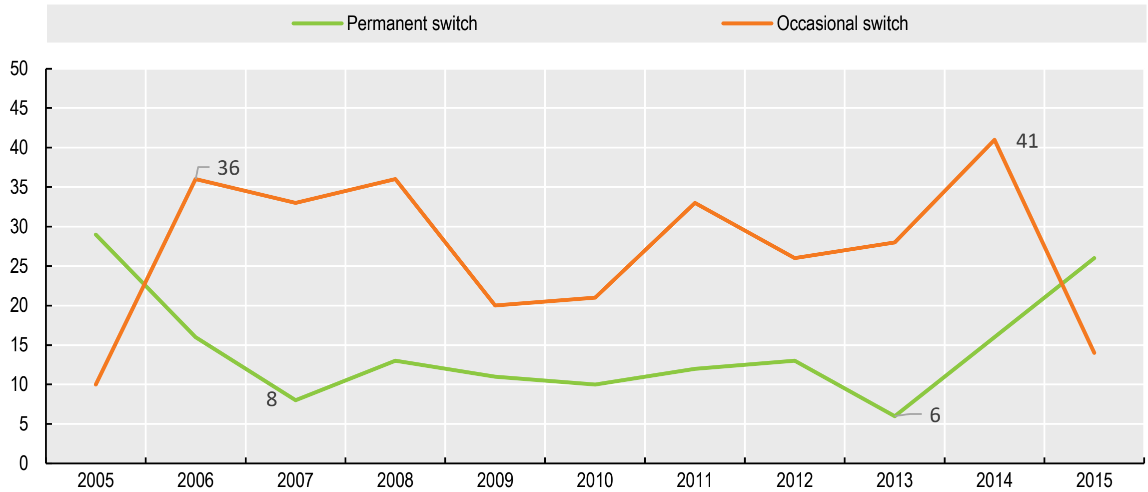
Notes: Markov chain analysis is applied to average shares 2005-2016 with the probability transition matrix in Table 26. Technically, the implied shares at convergence represents the eigenvector of the matrix corresponding to Eigen value equal to 1.

Characteristics of policy improvers

Many forward switching dairy farms in Norway show a higher productivity level compared to non-switching dairy farms with the difference significantly increasing over the time period considered. The rate of technical change is also slightly higher. Forward switching farms not necessarily produce with a larger herd size and less family labour. Most forward switchers are, however, less environmentally sustainable than non-switchers. Some forward switching dairy farms, particularly if they start with lower productivity, also show a higher level of innovativeness compared to non-switching dairy farms (index 03).

Policy makers are mainly interested in improving farm performance permanently rather than just for one or two periods. Out of all Norwegian dairy farms in the sample only 6% permanently improve their performance throughout the time period considered and 12% improved it occasionally falling back again to a lower performing class. Figure 14 illustrates the development in the number of permanent improving versus occasionally improving dairy farms in the time period considered. The number of permanently improving farms is lower than the number of occasionally improving farms in almost all years considered.

Figure 14. Norwegian dairy farms: Permanent and occasional improvers



Note: Permanent switch: farms switching to a more productive class and remaining there or improving further. Occasional switch: farms switching to a more productive class but then fall back again to lower performing class.

The interest of policy makers is not only on forward switching farms but also on possible characteristics and factors for such a switching behaviour. To identify possible drivers for forward and permanent switching behaviour based on statistically robust correlations between farm characteristics and different performance dimensions a multivariate regression analysis has been conducted. Most of the results for all forward switchers are not statistically significant (Table 28). This implies a lack of common characteristics for those farmers that improve just temporarily. Therefore, the discussion is focused on the permanent improvers.

The probability of farms permanently switching to more productive classes is mainly correlated with differences in the indexes for farm structure, the level of innovativeness and diversification, as well as individual household and financial characteristics (Table 28, second column). The Norwegian dairy farms in the sample are more likely to permanently improve their performance if they cultivate land beside their dairy production and produce with a smaller herd size. This finding is further confirmed by the positive correlation of the probability to permanently improve with the diversity of production (indicated by a lower than average score for the Herfindahl index measuring production concentration).

More innovative dairy farms (predominantly indicated by net investment) are more likely to permanently switch to a higher performing class. Younger and also female farmers are more likely to permanently improve and off-farm income seems positively correlated with a permanent switch. Finally, dairy farms with less than average financial assets and less than average receipt of subsidies are more likely to permanently improve their productivity.

Table 28. Norwegian dairy farms: Drivers of occasional and permanent productivity improvement

Correlation between probability of improving and farm characteristics. Bivariate random parameter selection models (2005 to 2016)

Outcome Model	Forward switchers	Permanent improvers
01 Farm structure		
Family/hired labour ratio	0.0028	-0.0391
Herd size (LU)	0.0696	-2.2636**
Land endowment (ha)	-0.0893	3.6606**
02 Environmental sustainability		
Stocking density (LU per ha)	-0.0476	1.3159*
Chemicals use (EUR per ha)	-0.1832**	-0.3487
Organic (probability)	0.0712	-0.2557
Environmental subsidies (EUR per ha)	0.0332	1.2663**
03 Innovation-commercialisation		
Net investment ratio (per total assets)	0.0813	1.4564**
Share land rented	0.0288	-0.3602*
Contract farming (prob)	-0.0317	-0.5932**
04 Technology		
Capital / labour ratio (EUR per AWU)	0.0527	0.7489*
Capital per cow (EUR per LU)	-0.0059	0.5564
Fodder per cow (EUR per LU)	0.1357	0.1069
05 Diversity		
Herfindahl Index (sqrt[Σ(yi/Y)2])	-0.4106***	-1.1505***
06 Individual		
Age (years)	-0.0768	-1.8875**
Gender (0-male, 1-female)	-0.0330	1.2633**
07 Location (Index score)	0.0938	-0.7586**
08 Household		
Female/male labour ratio	0.3201	3.3021*
Off-farm income (EUR)	0.2503***	1.9314***
09 Financial		
Total assets (EUR)	-0.0365	-2.5643**
Total subsidies (EUR)	-0.0118	-1.8448**

Note: *significant at 10%, **significant at 5%, ***significant at 1%.
Source: Estimations. The estimates for the selection equation are not shown here.

Main findings from the Norwegian dairy farms case study

In summary, a large share of dairy farms in Norway are in the most productive farm class 3 (65%), but this share decreases over the years. The productivity has increased in all farm classes, but also the differences in productivity across classes have increased. Backward switches are more frequent than forward switches and most forward changes are occasional rather than permanent. The current dynamics lead to a further relatively small reduction in the share of most performing class 3 of about two percentage points. The probability of permanently switching to more productive classes is mainly driven by farm structure (smaller herds) and the level of innovativeness and diversification, and female young farmers are more likely to see their farms permanently switching forward.

2. Policy impact analysis

The dynamic performance analysis applied to case studies in Section 1 can be extended to policy impact analysis with the appropriate methodologies as described in Annex A. The main difficulty is finding appropriate control groups of farms that have not experienced the policy change under consideration. These methodologies are particularly innovative and have been applied to two different policy examples: the different implementation of the 2003 reform of the Common Agricultural Policy in France and the United Kingdom, and the introduction of dairy payments in the Czech Republic. The first case provides very promising results in terms of policy impacts, while the second shows the limits when the method is applied on small samples.

2.1. CAP Pillar I implementation differences: The United Kingdom versus France

The 2003 reform of the EU Common Agricultural Policy (CAP) was decided in June 2003 and implementation began in 2004. One of the main features of the reform was the creation of the Single Farm Payment scheme that was implemented from 2005 in the United Kingdom and from 2006 in France. The 2003 CAP reform included adjustments to the common market organisations (CMO) for crops, beef and dairy products, replacing part or all of the existing premia under different CMOs. Farmers were allotted payment entitlements based on historical reference amounts received during the period 2000-02. Member States were given the option of defining the level of the payment at farm level or a regional level, and they also had the option of keeping linked to production up to 25% of the precedent per hectare payments in the arable sector.

Countries took different decisions on the modalities of the application of the reform. France took the decision of keeping the maximum possible share of the payments as coupled fixing the level of the SFP based on farm historical payments. On the other hand the United Kingdom took the decision of maximum decoupling (except for Scotland that applied partial decoupling), allowing more adjustment to market forces. In terms of the SFP level, different options were taken inside the United Kingdom: farm level historical payments in Scotland and Wales, and hybrid regional-farm level in England and Northern Ireland. All farms in the UK sample that were retained in the matching analysis are located in England[3] and, therefore, were subjected to full decoupling and hybrid regional-farm payments. Did this differing implementations have implications for the productivity and other performance characteristics of French crop farms compared to those in the United Kingdom? The analysis in this section isolates the impact of the different implementation package in France (75% of payments decoupled and paid at historical rates) and England (full decoupling and hybrid regional-farm level rates).[4]

[3] The UK sample used in the analysis in Section 1 contained farms in England and Wales. All specialised arable farms were used for matching in this section. However, no Welsh farm was matched to a French farm, indicating structural differences between Welsh and French agriculture. Consequently, the DID analyses were done for selected English and French farms only.

[4] Other policy factors in the package include the different conditionality in England and France and cross effect due to different policy treatment in other sectors like livestock. However those are unlikely to be main drivers of the different productivity dynamics in the two countries.

Propensity score matching (PSM) is applied to ensure that the farms to be compared in the cross-country DID-setting share similar characteristics before decoupling was implemented differently in France and the United Kingdom. Taking a look at descriptive statistics in the pre-treatment year 2003 suffices to understand the necessity of this approach: English crop farms are on average larger than French crop farms (259 ha versus 147 ha) and operate with a different capital and material structure (e.g. depreciation costs per hectare were EUR 162 in the United Kingdom compared to EUR 271 in France). These structural differences are considered to be the result of differing historical patterns with respect to cultural, institutional and governance related developments (Neuenfeldt et al., 2019[11]), locational and agri-ecological characteristics (Chau and de Gorter, 2005[12]); (Neuenfeldt et al., 2019[11]), productivity growth (Harrington and Reinsel, 1995[13]), farm household specifics and path dependencies (Zimmermann and Heckelei, 2012[14]; Mennig and Sauer, 2019[15]) or varying national agricultural policies (Ben Arfa et al., 2015[16]).

After matching individual crop farms in the two countries, significant differences of covariates which can be expected to affect the DID outcome variable for France and UK based farms are removed by balancing variables using the estimated propensity score. In this case, the propensity score is the conditional probability for a farm being located either in France or the United Kingdom. This matching model is estimated using a logit regression, with results reported in Table 29. It is statistically significant at the 1% level or higher as measured by the likelihood ratio test. Around 97% of all observations are correctly classified (98.60% for France, 89.27% for the United Kingdom). The regression model's estimates provide the basis for calculating the propensity score for each farm, which is then used for balancing observations between the French and UK samples.

In total, 33 UK crop farms (all in England) were matched to 33 French crop farms. The comparatively small matched sample is a result of structural differences between the two countries' agricultural sectors and of a relatively low number of observations in the UK sample. A sample of 33 farms per country cannot represent the whole arable farm sector and the results need to be interpreted with care.[5] Table A1 in Annex A reports unadjusted and adjusted means of covariates among English and French crop farms for the pre-treatment year 2003. After matching, the differences between farms in both countries are much smaller and only for a few cases significantly different from zero (5% significance level) which is also confirmed by additional robustness checks (e.g. the standardised bias SB indicator).

Crop farmers in England and France may differ in unobserved dimensions like environmental awareness or managerial attitude and ability. If these characteristics are not taken into account, the comparison between farms in both countries will lead to biased estimates for the policy treatment effect. Yet, variables like environmental preferences or managerial ability are not measured in the dataset and thus cannot be controlled for. In order to solve this problem, it is assumed that the effect of these unobservable factors on farm practices is constant through time.

Subtracting the difference in practices estimated by matching before implementation of the decoupling policy from the difference estimated after implementation gives the difference-in-difference estimate. Assuming that selection bias on unobservable variables is constant over time implies assuming that the average English crop farmer and his average French twin would have behaved in the same manner in the absence of decoupling (i.e. the common trend assumption).[6] According to the relevant literature,

[5] The matched sample consists of 66 farms, whose performance is measured over a period of six years, resulting in 396 observations. However, the datasets used are the most comprehensive and qualitatively most advanced that are currently available for both countries. Nevertheless, the results are convincingly backed up by the outcome of a battery of statistical tests and robustness checks.

[6] A key underlying concept of the difference-in-difference method is the parallel trends assumption. This assumption states that the untreated units represent the appropriate counterfactual in terms of the general trend that the treated units would have followed had they not been treated. For this reason, both comparability and common trend assumption have to be checked for the two countries. Similar natural conditions (soil quality, precipitation, temperature etc.) and similar macroeconomic and policy trends have been considered. Additionally, we performed common trend tests for our main outcome variable 'productivity' in a sense that we ran DID fixed effects regressions for a period preceding the treatment period (1997-2002) and for a period following it (2009-2013). In both cases, no significant differences in the productivity development were found. Several tests were performed to check the validity of our results. First, our latent class estimates were subject to AIC and SBIC tests to decide about the number of classes. First-order elasticities show the expected sign in most groups and for most inputs. Second, when applying the PSM method, variable selection and common support were checked and the best matching algorithm was chosen in terms

e.g. (Boninger, Krosnick and Berent, 1995[17]; Deary et al., 2000[18]) the common trend assumption is plausible, because especially unobserved determinants like important attitudes and individual differences in measures of mental ability are usually stable over time. Furthermore, the general CAP framework affects the United Kingdom and French agricultural sectors equally and both countries follow similar macroeconomic trends in the study period 2003-08 which additionally support the common trend assumption for this study.

Table 29. French and English crop farm matching

Logit regression model based PSM

Covariate	Estimate
Utilised agricultural area	0.012***
Labour	-0.337
Total assets per ha	0.001***
Total output per ha	0.001***
Depreciation costs per ha	-0.023***
Expenditures for fertilisers and pesticides per ha	-0.019***
Energy expenditures per ha	0.050***
Expenditures for other materials per ha	-0.001
Net investment per ha	-0.002**
Expenditures for contract work and machinery hire per ha	0.005**
Environmental subsidies per ha	0.008
Intercept	-2.518***
Model Quality	
Number of observations	1055
LR Chi-squared	847.08***
Prob > Chi-squared	0.000
Pseudo R-squared	0.815
% correct predictions	96.78

Note: *significant at 10%, **significant at 5%, ***significant at 1%.
Source: Estimations.

Figure 15 illustrates the general productivity development for English and French crop farms over the full time period considered. Generally, English crop farms show a significantly stronger productivity increase between 2003 and 2008 compared to French crop farms, even if there is some catching up by the French at the end of the period. Crop farms in England increased their productivity by more than 5.3% in total compared to about 2.9% improvement for crop farms in France in the same time period. Figure 16 shows the development of technical change for English crop farms versus French crop farms between 2003 and 2008. It shows that the technical change rates are positive for both countries during this period with a significantly higher rate for English crop farms for the first four years (up to 2006). However, the technical change rate for crop farms in England (slightly) decreased from 2004 on, whereas the technical change rate for crop farms in France (slightly) increased over the full period investigated.

of bias reduction. Third, the robustness of the DID estimator was assessed by step by step adding control variables and by performing mock DID estimates for different periods, which included checks on alternative base years. These robustness checks largely confirmed the results obtained. Annex A includes some of these details.

Figure 15. Productivity development of matched English and French crop farms

2003 to 2008, log values

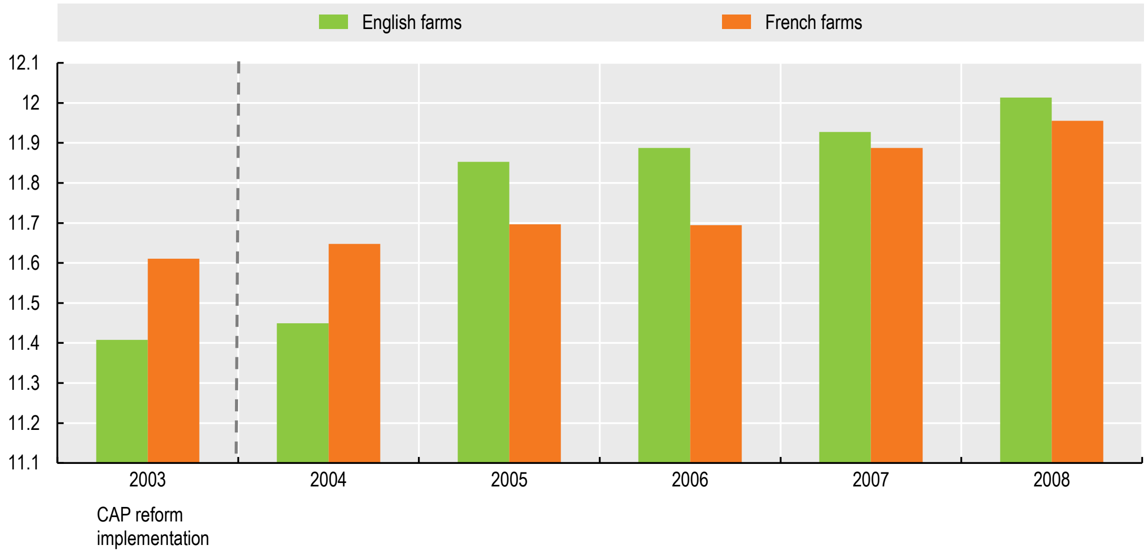
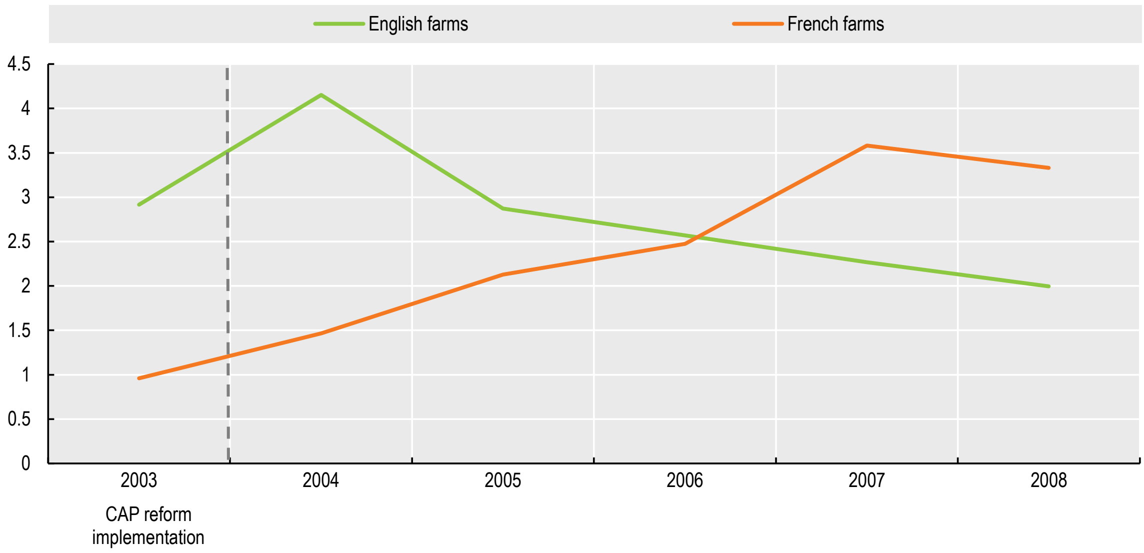


Figure 16. Technical change development of matched English and French crop farms

2003 to 2008, percentage change p.a.



The estimates for the effect of policy decoupling on crop farms' productivity in the United Kingdom and France are summarised in Table 30 (see estimate for "DID policy effect indicator = 0.18"). This statistically robust estimate for the effect of the policy change in England compared to France suggests that the full decoupling approach had a positive and statistically significant effect on English crop farms' productivity level during the period investigated (2003-2008). French crop farms are used as a control group, hence, the results imply that the productivity effect of the decoupling approach in France (i.e. a minimum decoupling) induced a less significant impact than the approach followed in England. The estimate could be also interpreted in terms of a significant productivity add on by the higher degree of decoupling followed in the United Kingdom.

Table 30. Estimates for policy effect on crop farms' productivity

Outcome variable productivity level (2003 to 2008), DID policy effect indicator (bold) indicates policy effect on productivity level

Covariate	Estimate
DID policy effect indicator	**0.180*** **
Year2003	-0.346***
Year2004	-0.375***
Year2005	-0.184***
Year2006	-0.178***
Year2007	-0.067**
Share arable land	0.492***
Share off-farm income	-0.312***
Ratio hired labour/family labour	0.148***
Subsidies per ha	-0.001**
Environmental subsidies per ha	0.001
Organic farming	-0.179*
Model Quality	
Number of observations	396
Constant	11.419***
Prob > F	0.000
Within R-Squared	0.674

Note: *significant at 10%, **significant at 5%, ***significant at 1%.
Source: Difference-in-Difference Fixed-Effects Regression Estimations.

The estimates for the policy effect on crop farms' technical change in the United Kingdom and France are summarised in Table 31 (see estimate for "DID policy effect indicator = -0.009"). The statistically robust estimate for the effect of the decoupling policy in England suggests, however, a slightly negative effect on technical change during the period investigated (2003 to 2008). Compared to the policy effect on productivity this result is, at first glance, surprising. However, considering the different components of farm level productivity (i.e. technical change, technical efficiency, and scale efficiency) it suggests that the identified productivity enhancing effects are primarily based on efficiency and scale improvements and not primarily on farms' adoption of new technologies.

Hence, according to the results in this analysis, the full decoupling approach with hybrid regional-farm level rates in the United Kingdom effectively incentivised crop farms to further optimise their scale of crop production activities to decrease their average cost of production and hence, increase profitability. Furthermore, these results imply that those crop farms, taking advantage of the additional freedom adjust under decoupling, apparently moved closer towards the optimal crop production frontier during that period which resulted in significant technical efficiency gains. These results are confirmed by the results on dynamic performance in Section 1. The switches forward to more productive classes is more frequent among UK[7] crop farms, than the switches backwards and most of the switches forward are permanent rather than occasional. The opposite is true for French crop farms. Both French and UK farms experience a reduction in the number of switches around the reform period, probably due to the uncertainty associated with the reform, marking a structural change. However, while French farm dynamics slowed down the change in farm classes shares, UK farms have an implicit positive evolution towards the most productive class 3 that seem to be sustained in the long term.

[7] The UK samples used in Section 1.4 includes farms from England and Wales.

Table 31. Estimates for policy effect on technical change

Outcome variable technical change (2003 to 2008), DID policy effect indicator (bold) indicates policy effect on technical change estimate

Covariate	Estimate
DID policy effect indicator	**-0.009*** **
Year2003	-0.019***
Year2004	-0.005***
Year2005	-0.004***
Year2006	-0.004**
Year2007	0.001
Share arable land	0.006
Share off-farm income	0.013***
Ratio hired labour/family labour	0.002
Subsidies per ha	0.000***
Environmental subsidies per ha	-0.000***
Organic farming	-0.010
Model Quality	
Number of observations	396
Constant	0.019*
Prob > F	0.000
Within R-Squared	0.352

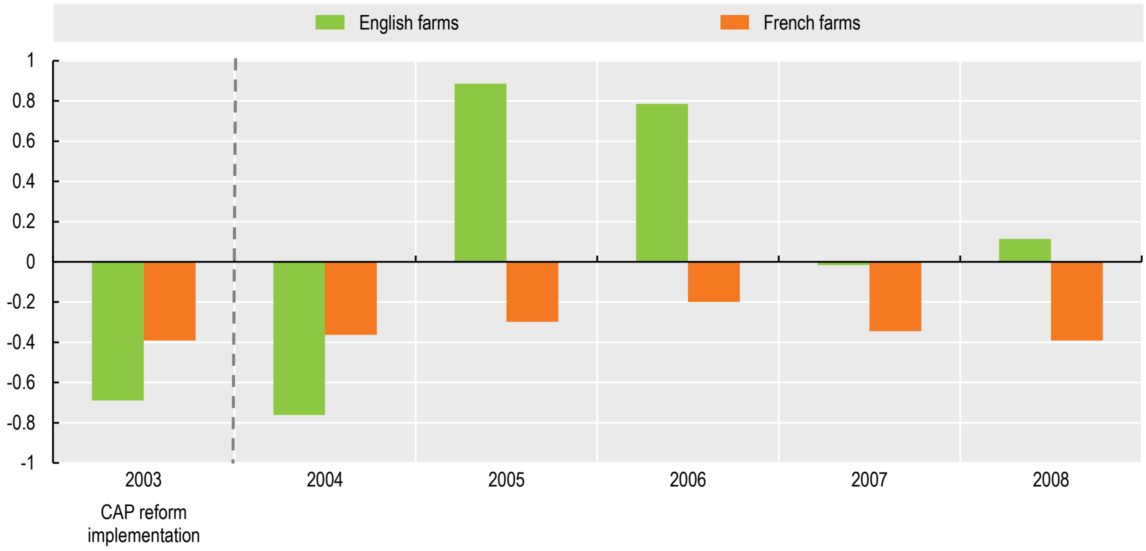
Note: *significant at 10%, **significant at 5%, ***significant at 1%.
Source: Difference-in-Difference Fixed-Effects Regression Estimations.

These findings are confirmed by the results for potential policy effects on other crop farm performance indicators (i.e. diversity of production, innovativeness, farm structure, environmental sustainability, and technology intensity). The results for the difference in the effect on the diversity of production for crop farms in England and France are summarised in Figure 17. Generally, English crop farms show a significantly stronger increase in the diversity of production structure between 2003 and 2008 compared to French crop farms. The estimate for the "DID policy effect indicator" indicates a statistically significant and positive effect on crop farms' production diversity by the full decoupling in the United Kingdom during the time period investigated. This may be driven by the opportunities provided by more production freedom under decoupled payments.

The potential effect on other crop farm performance indices was also tested e.g. farm structure, environmental sustainability, innovativeness and technology intensity by using a similar analytical set-up. However, no significant effects were found for other farm performance indicators with respect to the difference in the implementation of decoupling in the United Kingdom and France during the time period investigated. The non-significant effect on crops farms' innovativeness is consistent with the finding for the slightly negative policy effect on crop farms' technical change over the period considered. Overall, it can be summarised that, according to the DiD analysis, the full decoupling approach in England with hybrid regional-farm level rates enhanced the productivity development of crop farms compared to a control group of French crop farms experiencing a lower degree of decoupling of payments with historical rates. In sum, the significant positive effects on crop production scale and crop production efficiency by the full decoupling policy in the United Kingdom outweighed potential negative effects on technical change during this period 2003 to 2008.

Figure 17. Diversity index development of matched English and French crop farms

2003 to 2008



2.2. Dairy farming subsidies in the Czech Republic

In a second policy case study, the effect of two payments promoting dairy farming in the Czech Republic have been analysed. Introduced in 2010 at national level, a payment was granted per cow with the objective of strengthening the competitiveness of Czech dairy farms ("specific market support measure in the dairy sector" based on EC Regulation 1233/2009 focusing specific market support measures in the milk and milk products sector).[8] Also introduced in 2010 at national level, a second payment was granted per cow ("payment for cows kept under the dairy market (dairy cows)" based on EC Regulation Art. 68 of the NR (EC) No 73/2009.[9] There is no theoretical basis to presume that such a payment would have an impact on productivity.

Since all Czech dairy farmers equally profited from these payments, a control group for the proposed DID setting does not exist at a national level. At EU level, though, dairy farmers in countries such as Poland, Slovakia or the Baltic states face agricultural, natural and socio-economic structures that are quite similar to the ones in the Czech Republic. More importantly, they share similar institutional and policy experiences by communist policy regimes until 1991 and have equally been affected by the EU's CAP since joining the European Union in 2004. These structural and institutional pre-conditions give strong support for assuming "overall common trends", a prerequisite assumption to hold for DID analyses to deliver significant and

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[8] All subsidies are paid through the State Agricultural Intervention Fund (SAIF). The rate for calculating the support is determined on the basis of the proportion of the funds set by the Czech Republic by Commission Regulation (EU) No 1233/2009 and the total quantity of milk or milk products delivered or sold by the applicant during the reference period. The rate is CZK 0.3672 per 1 kg of milk.

[9] The SAIF rules for granting the subsidy, example for 2011: "The payment shall be granted for the total number of LU's determined by the number of dairy cows kept on 31.3.2011. The conversion rate to determine the number of LU's shall be 1,0 (1 dairy cow = 1 LU) milk (dairy cows) on a holding registered in the central register, with the lowest number for payment being 2 LUs. The Fund shall only grant payment if the proportion of the income or revenue for milk sold in the total income or income from agricultural production for the calendar year preceding the date of application is greater than or equal to 15%. If the proportion of income or revenue for milk sold in total income or income from agricultural production is greater than or equal to 30%, the applicant shall be entitled to payment at the rate of 100%. If the proportion of income or revenue for milk sold in total income or income from agricultural production is greater than or equal to 15% and less than 30%, the applicant shall be entitled to a payment of 50% of the full rate. Payment shall not be granted for those cows for which a payment has already been applied for the production of suckler cows."

robust results. Given data availability, a control group has been selected from a sample of Estonian dairy farms.

Similar to the previous policy effects analysis, propensity score matching (PSM) is also applied to ensure that the farms to be compared in the cross-country DID-setting share similar characteristics before the payments were implemented differently in the Czech Republic and Estonia (for a more detailed outline of the analysis applied, see Annex A). Due to a very limited data availability, in total, only seven Czech dairy farms were matched to seven Estonian dairy farms. Table 32 reports the estimates for the corresponding matching model. It is statistically significant at the 1% level or higher as measured by the likelihood ratio test. The regression model's estimates provide the basis for calculating the propensity score for each farm, which is then used for balancing observations between the Czech and Estonian dairy farm samples.

Table 32. Czech and Estonian dairy farm matching

Logit regression model based PSM

Covariate	Estimate
Utilised agricultural area	-2.842**
Labour per ha	1.856*
Total assets per ha	1.675
Expenditures for fertilisers and pesticides per ha	0.109***
Cow per ha	1.672
Total output per ha	1.464
Age	-4.952*
Fodder per cow	-0.003*
Share rented land	6.788***
Share grassland	4.523**
Intercept	-10.636
Model Quality	
Number of observations	110
LR Chi-squared	108.14***
Prob > Chi-squared	0.000
Pseudo R-squared	0.756
% correct predictions	95

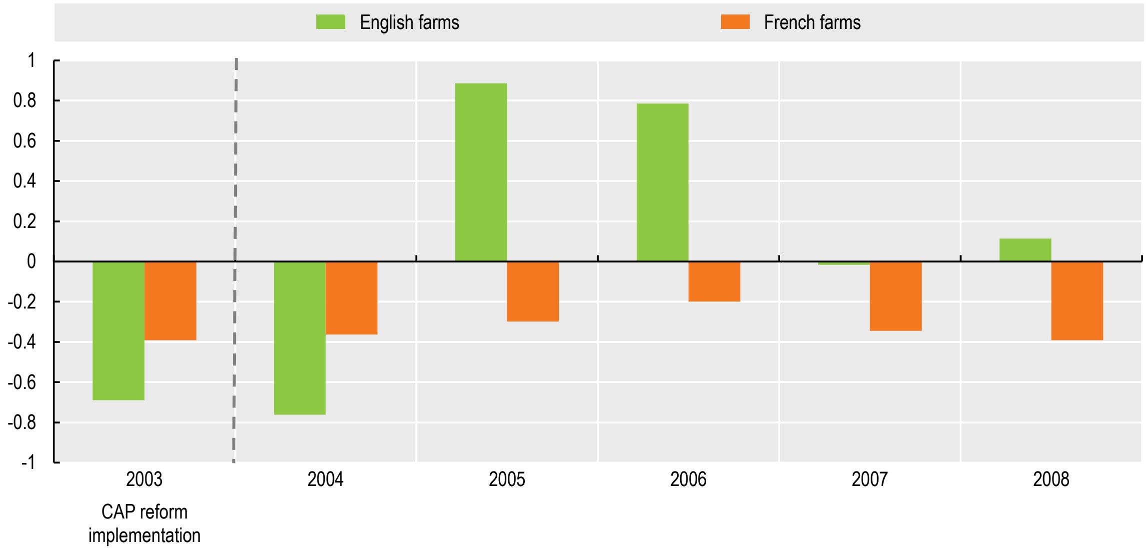
Note: *significant at 10%, **significant at 5%, ***significant at 1%.
Source: Estimations.

The policy effects on dairy farms' productivity, sustainability and diversity in the Czech Republic and Estonia have been calculated. The estimates for the "DID policy effect indicator" suggest that the dairy subsidisation policy in the Czech Republic had a positive effect on the Czech dairy farms' productivity level and sustainability index during the period investigated (2009 to 2015) but a negative effect on their production diversity. However, the very limited sample size and potentially weak comparability of treated and control samples, suggest to use these results very cautiously. The statistical significance seems not appropriate given these limitations to draw robust and reliable policy conclusions based on these empirical findings.

Figure 18 illustrates the general productivity development for Czech and Estonian dairy farms over the time period considered. Generally, Czech dairy farms do not show a significantly stronger productivity increase or less significantly decrease in the sustainability index between 2009 and 2015 compared to Estonian dairy farms. This is further evidence for a limited robustness and reliability of the policy effect estimates for this case study. This example shows the limits of the method, in particular when matching samples are small and the analytical basis for testing an hypothesis on impacts on productivity are therefore weak.

Figure 18. Productivity level development of matched Czech and Estonian dairy farms

2009 to 2015



Annex A. Detailed methodology and additional information

Class characteristics' analysis

It is of high policy importance to be able to identify high and low performing farms to efficiently design and effectively target sectoral policies with respect to economic performance, environmental sustainability and innovativeness of the individual farms. In addition to the characteristics reported in Part I of the project (OECD, 2020[3]), core production and technology and other characteristics are summarised, as well as performance indices' scores per class at the beginning, the midpoint and the end of the respective period considered (i.e. at t=1, t=n/2, and t=n) by means of descriptive statistics (mean, minimum, maximum, standard deviation, quantiles' values per class, etc.).

In order to analyse the marginal contribution of the individual characteristics to the relative probability of class membership P_{ij} an appropriate qualitative response model will be specified and estimated.

Model 1: A corresponding multinomial logit model can be exemplary specified as follows for a cross-sectional setting:

$$P_{ij} = \frac{exp(\alpha_j + X_i\beta_j)}{\sum_{k=1}^{J} xp(\alpha_k + X_i\beta_k)} \qquad [1]$$

where P_{ij} is the probability of class membership for farm i, α_j denotes the specific constant term of class membership j (with j = class 1, class 2 and class 3, respectively), and X_i is a set of individual farm characteristics (see also initially (McFadden, 1974[19]), or for an exemplary application, e.g. Zhu et al. (2010[17]).

This first stage of the analyses will focus on exemplary country cases for the sectors dairy, crops, pigs and mixed crop-livestock farming (Table 1.1 in (OECD, 2020[2])). The selection of country cases is meant to consider the variety of production settings and technology environments across the countries that participate in this OECD FLA project. Hence, the aforementioned analysis for the following country and sector cases will be completed: France (crop farming), the United Kingdom (crop farming), Denmark (dairy farming), Australia (crop farming, dairy, cattle, sheep and mixed farming).

Class dynamics' analysis

The second stage of the proposed analysis in phase II will focus on the dynamics in farms' class membership over the time period investigated. Initiating and supporting farms' switch to a more productive class is a primary policy goal. However, potential trade-offs and/or synergies between economic and environmental performances are crucial to be considered by policy makers. Furthermore, it is important to know what type of farms are actually switching to more productive and/or more sustainable and/or more innovative classes and what type of farms are actually maintaining these higher performance levels over time given sector and country specifics as well as potential external shocks.

First, the characteristics of farms that switch to a different class during the respective time period considered on a yearly basis (i.e. from one year t to the next year t+1) are summarised. Groups were created for "positive switchers" (i.e. farms that switch to a more productive class from one year *t* to the next year *t+1*), for "negative switchers" (i.e. farms that switch to a less productive class), and for "non-switchers" (i.e. farms that stay in the same class). Core production and technology and other characteristics are summarised, as well as performance indices' scores for those farm groups.

Second, the characteristics of farms that switch to a more productive class and manage to remain in this class for a certain time or even improve further are identified and summarised. Due to specific sampling characteristics (i.e. rotational surveying) individual farms may not be in the sample for the full time period investigated. Hence, the sub-sample is analysed of switching farms that are part of the sample for at least three years in a row during the respective time period considered.

A group of “permanent improvers” was created, i.e. farms that switch to a more productive class from one year to the next year and remain there also in the subsequent year or improve even further (i.e. manage to switch again to a more productive class in the remaining period of their individual sample membership). Another group was set up of “occasional improvers” which are farms that switch to a more productive class from one year to the next year but then fall back to a less productive class again.

For example, assuming that class 1 represents the least productive, class 2 the medium productive, and class 3 the most productive class, Table A.1 illustrates class switching scenarios for the two groups.

Table A.1. Class switching scenarios

Time point	Year t	Year t+1	Year t+2
Group I “permanent improvers”			
Class membership	1	2	3
	1	2	2
	1	3	3
	2	3	3
Group II “occasional improvers”			
Class membership	1	2	1
	1	3	2
	1	3	1
	2	3	2
	2	3	1

Note: class 1= least productive, class 2 = medium productive, and class 3 = most productive.

The third step in this 2nd stage analysis refers to the estimation of the propensity to switch to a more productive class in the respective time period as well as correlated farm characteristics. Therefore, two econometric estimation models are specified:

Model 2: In order to analyse the relative probability P_{is} of switching to a different class from year t to year t+1 as well as the marginal contribution of individual farm and farmer characteristics an appropriate qualitative response model will be specified and estimated. Again, a multinomial logit model seems appropriate to estimate this probability conditional on a set of marginal characteristics. Such a model can be exemplary specified as follows for a cross-sectional setting:

$$P_{is} = \frac{exp(\alpha_s + X_i\beta_s)}{\sum_{m=1}^{S} xp(\alpha_m + X_i\beta_m)} \quad [2]$$

where P_{is} is the probability of a certain class switch for farm I from year t to t+1, α_s denotes the specific constant term of class switch s (with s = +1 for switch to more productive class, 0 for staying in the same class - i.e. no switch, -1 for switch to a less productive class, respectively), and X_i is a set of individual farm characteristics covering differences in characteristics from year t to year t+1, and levels as well as binary indicators for characteristics (see also initially (McFadden, 1974[19]), or for an exemplary application e.g. (Zhu et al., 2010[20]).

Model 3: This third model intends to further investigate the dynamic behaviour of productive farms. Here, the aim is to analyse the relative probability of switching to a more productive class (i.e. improving further) from year t+1 to year t+2. Hence, the focus is on those farms that have already improved their performance (i.e. a switch to a more productive class from year t to year t+1) and would like to estimate the probability of staying at the higher performance level (i.e. in the same productive class) or even improving further (i.e. a switch to an even more productive class from year t+1 to year t+2).

This model can be written as a system of equations for two latent (unobserved) variables:

$$y_i^* = X_i\beta_m + \varepsilon_i \quad [3]$$

$$d_i^* = Z_i\gamma_m + v_i \quad [4]$$

$$d_i = 1 \;\; if \;\; d_i^* > 0; \quad d_i = 0 \;\; otherwise \quad [5]$$

$$y_i = y_i^* * d_i \quad [6]$$

with i = 1, …, N. y_i^* denotes a latent outcome variable with observed counterpart y_i as the switch in classes between year t+1 and year t+2. d_i^* denotes a latent variable based on an indicator function d_i reflecting whether a switch to a more productive class has been observed from year t to year t+1 (i.e. capturing sample selection). The relationship between latent and observed dependent variables (d_i, d_i^*, y_i, y_i^*) y_i^* are shown in equations [5] and [6]. Equation [3] is of primary interest as it aims to estimate the probability of switching to a more productive class (i.e. improving further) from year t+1 to year t+2. X_i and Z_i are vectors of exogenous variables covering differences in farm and farmer characteristics from year t to year t+1, and levels as well as binary indicators for other characteristics. β_m and γ_m are a set of parameters to be estimated, and ε_i and v_i are zero mean error terms following $E[\varepsilon_i|v_i] \neq 0$ (see e.g. (Vella, 1998[21]) (Miranda and Rabe-Hesketh, 2006[22])).

In this context $y_i = +1$ reflects a farm's switch to a more productive class between year t+1 and year t+2, $y_i = 0$ reflects a farm's staying in the same class in year t+2 as in year t+1, and $y_i = -1$ and $y_i = -2$ reflect a farm's switch to less productive classes, respectively. Hence, the variable of interest, y_i takes on H ordered response categories $y_h, h = 1, \dots, H$ whereas the difference between any pair of categories has no immediate cardinal interpretation. Consequently, the following threshold model determines the observed response estimated by equations [6] and [3]:

$$y_i \begin{cases} y_1 \;\; if \;\; -\infty < y_i^* \leq -2 & i.e. farm\ i\ switches\ class\ 3\ to\ class\ 1 \\ y_2 \;\; if \;\; -2 < y_i^* \leq -1 & i.e. farm\ i\ switches\ class\ 3\ to\ class\ 2, or\ class\ 2\ to\ class\ 1 \\ y_3 \;\; if \;\; -1 < y_i^* \leq 0 & i.e. farm\ i\ does\ not\ switch\ classes \\ y_4 \;\; if \; 0 < y_i^* \leq \infty & i.e. farm\ i\ switches\ class\ 2\ to\ class\ 3 \end{cases} \quad [7]$$

Policy impacts

CAP Pillar I implementation differences: England versus France

This empirical case study investigates the effects of a well-known, trade-related policy reform aiming at reducing agricultural production surpluses through limiting the incentives to produce: decoupling. This policy measure essentially aims at breaking the linkages between farm income-support schemes and farmers' production decisions. Numerous previous work on the topic exists and is methodically very diverse (see for example (Galko and Jayet, 2011[23]); (Guyomard, Baudry and Carpentier, 1996[24]); (Hennessy, 1998[25]); (Kazukauskas et al., 2013[26]); (Serra et al., 2006[27]). However, most of the more robust contributions nevertheless lack a counterfactual approach.

The general lack of a counterfactual scenario is due to the fact that decoupling policies typically affect all farms. The 2003 CAP reform, which decoupled payments from production, was implemented in all EU Member States from 2004 onwards. However, not all Member States put the policy into practice to the same extent. Especially in France, the share of remaining coupled support was kept higher compared to other countries. The effect of a variation in the remaining share of coupled subsidies on farm productivity, technical change, resource allocation, innovativeness and sustainability can thus be studied comparing the performance of French farms to the performance of farms in the United Kingdom,[10] where decoupling

[10] The UK sample used in the analysis in Section 1 contained farms in England and Wales. All specialised arable farms were used for matching in Section 2.1. However, no Welsh farm was matched to a French farm, indicating structural differences between Welsh and French agriculture. Consequently, the DID analyses were done for selected English and French farms only and we refer in this section to English crop farms.

was implemented more stringently. The different outcomes can be compared to a scenario without decoupling based on literature findings.

Model 4: the two-period setting was applied to exemplify the analytical approach as follows: $t = 2003$ refers to the period before the CAP reform has been implemented whereas $t = 2004$ refers to the period after the reform's implementation. $Y_t^{UK\_cpI}$ and $Y_t^{F\_gpI}$ be the respective outcomes for English crop farms after the complete reform (UK_cpI) and crop farms in France after gradual reform (F_gpI) at time t. Hence, the DID method estimates the average UK reform programme impact as follows:

$$DID_{UK\_cpI} = E\left(Y_{2004}^{UK\_cpI} - Y_{2003}^{UK\_cpI} \middle| T_{UK\_cpI} = 1\right) - E\left(Y_{2004}^{F\_gpI} - Y_{2003}^{F\_gpI} \middle| T_{UK\_cpI} = 0\right) \quad [8]$$

where $T_{UK\_cpI} = 1$ denotes treatment or the presence of the complete CAP reform implementation at $t = 2004$ or after, whereas $T_{UK\_cpI} = 0$ denotes untreated farms. Given the panel data availability at crop farm level farm performance impacts can be estimated by assuming that unobserved heterogeneity over crop farms is time invariant and uncorrelated with the complete CAP pillar I reform treatment over time.

The DID estimator for the United Kingdom complete CAP pillar I reform introduced in 2004 can be expressed within a regression framework in its simplest form by the following equation:

$$Y_{it} = \alpha + \beta T_{iUK\_cpI} t + \rho T_{iUK\_cpI} + \gamma t + \varepsilon_{it} \quad [9]$$

where the coefficient β on the interaction between the post-programme treatment variable T_{iUK_cpI} and time $t = 1989,, \ldots, 2016$ gives the average reform related DID effect. This two-period model is further generalised by using multiple time periods applying a panel fixed-effects model including a range of time-varying covariates X_{it} related to farm and farmer characteristics. The applied matching procedure (i.e. propensity score matching) for the baseline data in t = 2003 makes certain that the crop farm comparison group is similar to the crop farm treatment group before applying double differences to the matched crop farm sample (i.e. with-without reform treatment and before-after reform treatment).[11] As outcome variable Y_{it} various farm productivity and other farm performance related indices are applied, including class membership and class switching indicators based on the results produced in phase I of this project.

Different matching estimators were tested (i.e. nearest neighbour matching with and without replacement, radius matching, kernel matching) as the performance of different matching algorithms largely depends on the data structure. They all give similar results, however, in terms of overall matching quality, nearest neighbour matching without replacement, random ordering and a caliper of (0.1), performed best. Results confirmed structural differences already detected descriptively. Based on the logit model's explanatory variables, the likelihood of a farm being located in England differs considerably for almost all observations. Nevertheless, certain farms in both countries share similar propensity scores. Given that many individuals of the sample fall outside the region of common support, however, treatment effect estimations have to be interpreted with caution.

Whether or not there is a significant difference in the economic performance over time as well as in the development of farm technology defining indices was then tested (especially concerning environmental sustainability, technology, innovation and diversity) between crop farms in England – where comparatively strong decoupling occurred – and their French counterparts facing a higher share of remaining coupled support. The impact of these differences in implementing the deregulation policy is measured using the matched samples outlined before.

[11] The robustness of the DID estimator was assessed by step by step adding control variables and by performing mock DID estimates for different periods, which included checks on alternative base years. These robustness checks largely confirmed the results obtained.

Table A.2. Before and after matching sample comparison

Pre-treatment year 2003

Covariates	**(1)** Potential comparison farms UK	**(2)** Potential comparison farms FR	**(3)** Selected comparison farms UK	**(4)** Selected comparison farms FR	**(5)** Bias before	**(6)** Bias after
Utilised agricultural area	258.7	146.7***	156.5	171.3	49.8	-6.6
Labour	3.2	1.9***	1.9	2.1	37.5	-4.1
Total assets per ha	7429.1	2830.6***	3437.9	3313.1	115.8	3.1
Total output per ha	1334.1	1393.3	1268.3	1181.5	-2.8	4.0
Depreciation costs per ha	162.0	271.4***	173.3	153.2	-38.5	7.1
Expenditures for fertilisers and pesticides per ha	215.1	294.9***	228.4	234.3	-49.4	-3.6
Energy expenditures per ha	126.1	59.2***	93.0	93.3	94.2	-0.4
Expenditures for other materials per ha	16.5	17.3	13.6	12.4	-0.6	1.1
Net investment per ha	234.0	550.2***	340.3	329.8	-63.0	2.1
Expenditures for contract work and machinery hire per ha	73.8	66.0	85.1	82.7	8.7	2.7
Environmental subsidies per ha	16.8	7.8***	9.3	2.9	22.6	16.2
Number of observations	850	205	33	33		

Note: significantly different means between observations from the potential (selected) group in the UK and from the potential (selected) control group in France in a t-test for equality of means at the 10% (*), 5% (**) and 1% (***) level are indicated.
(5) and (6): Following (Rosenbaum and Rubin, 1985[28]), for a given covariate X, the standardised difference before matching is the difference of the sample means in the full treated and non-treated subsamples as a percentage of the square root of the average of the sample variances in the full treated and non-treated groups. The standardised difference after matching is the difference of the sample means in the matched treated (that is, falling within the common support) and matched non-treated subsamples as a percentage of the square root of the average of the sample variances in the full treated and non-treated groups.

Dairy farming subsidies in the Czech Republic

All Czech dairy farmers equally profited from these payments, hence, a control group for the proposed DID setting does not exist at a national level. At EU level, though, dairy farmers in countries such as Poland, Slovakia or the Baltic states face agricultural, natural and socio-economic structures that are quite similar to those in the Czech Republic. More importantly, they share similar institutional and policy experiences by Soviet influenced policy regimes until 1991 and have equally been affected by the EU CAP since joining the European Union in 2004. These structural and institutional pre-conditions give strong support for assuming "overall common trends", a prerequisite assumption to hold for DID analyses to deliver significant and robust results. Given data availability, a control group has been selected from a sample of Estonian dairy farms.

Model 4.1: the two-period setting can be used to exemplify the analytical approach as follows: $t = 2009$ refers to the period before the dairy cow related subsidies programmes have been implemented whereas $t = 2010$ refers to the period after the programmes' implementation, letting $Y_t^{Cz\_dc}$ and $Y_t^{Est\_ndc}$ be the respective outcomes for the Czech dairy farms benefiting from the programmes (Cz_dc) and non-treated dairy farms in Estonia (Est_ndc) at time t. Hence, the DID method estimates the average Czech dairy cow subsidies' programme impact as follows:

$$DID_{Cz\_dc} = E\left(Y_{2010}^{Cz\_dc} - Y_{2009}^{Cz\_dc} \middle| T_{Cz\_dc} = 1\right) - E\left(Y_{2010}^{Est\_ndc} - Y_{2009}^{Est\_ndc} \middle| T_{Cz\_dc} = 0\right) \quad [10]$$

where $T_{Cz\_dc} = 1$ denotes treatment or the presence of the dairy cow related payment programmes change at $t = 1$, whereas $T_{Cz\_dc} = 0$ denotes untreated farms. Given the panel data availability at dairy farm level farm performance impacts can be estimated by assuming that unobserved heterogeneity over dairy farms is time invariant and uncorrelated with the dairy cow related subsidies treatment over time.

The DID estimator for the Czech dairy cow subsidies programmes introduced in 2010 can be expressed within a regression framework in its simplest form by the following equation:

$$Y_{it} = \alpha + \beta T_{iCz\_dc} t + \rho T_{iCz\_dc} + \gamma t + \varepsilon_{it} \quad [11]$$

where the coefficient β on the interaction between the post-programme treatment variable T_{iCz_dc} and time $t = 2005, \dots, 2015$. gives the average cow subsidies related DID effect. This two-period model is further generalised by using multiple time periods applying a panel fixed-effects model including a range of time-varying covariates X_{it} related to farm and farmer characteristics. The applied matching procedure (i.e. propensity score matching) for the baseline data in t = 2009 ensures that the dairy farm comparison group is similar to the dairy farm treatment group before applying double differences to the matched dairy farm sample (i.e. with-without dairy cow related subsidies treatment and before-after dairy cow related subsidies treatment). As outcome variable Y_{it} various farm productivity and other farm performance related indices are applied, including class membership and class switching indicators based on the results produced in phase I of this project.

Annex B. Farm dynamics case studies: Detailed descriptive statistics

Table B.1. Australian crop farms: Performance classes

Descriptive statistics and estimates (1989 to 2018)

	Performance class 1 Most productive (phase I class 1, 87.6%)	Performance class 2 Least productive (phase I class 2, 12.4%)
Performance		
Estimated Values		
Productivity level (AUD per year)	641 715	196 596
Technical change (% p.a.)	0.236	-0.716
Characteristics		
Deviations from Standardised Sample Means[1]		
Farm structure (index 01)		
Family/hired labour ratio	-0.0063	0.0446
Land (ha)	-0.0020	0.0141
Form of ownership (1=company, 2=partnership/trust, 3=sole trader)	-0.0290	0.2047
Environmental sustainability (index 02)		
Fuel per ha (AUD per ha)	0.0278	-0.1959
Chemicals use (AUD per ha)	0.0656	-0.4632
Innovation-commercialisation (index 03)		
Net investment ratio (per total assets)	0.0274	-0.1934
Contract farming (1=yes, 0=no)	0.0783	-0.5527
Share land rented	0.0341	-0.2405
Technology (index 04)		
Capital / labour ratio (AUD per AWU)	0.0021	-0.0149
Capital per ha (AUD per ha)	-0.0105	0.0074
Seed per ha (AUD per ha)	0.0160	-0.1132
Diversity		
Herfindahl Index (sqrt[Σ(yi/Y)2])	0.1884	-1.3297
Production diversity (yc/ ΣY)	0.1884	-1.3237
Individual		
Age (years)	-0.0151	0.1065
Education (various levels)	0.0362	-0.2554
Gender	0.0049	-0.1135
Location		
Region pastoral zone	-0.0218	0.1537
Region wheat-sheep zone	0.0404	-0.2851
Region high-rainfall zone	-0.0271	0.1910
Household		
Off-farm income share	-0.0393	0.2776
Age spouse (years)	0.0058	-0.0411
Education spouse (various levels)	0.0354	-0.2500
Gender spouse	0.0248	-0.1749

	Performance class 1 Most productive (phase I class 1, 87.6%)	Performance class 2 Least productive (phase I class 2, 12.4%)
Financial		
Total assets (AUD)	0.0430	-0.3039
Total subsidies (AUD)	-0.0105	0.0739
Equity/debt ratio	-0.0117	0.0827

Note: AWU: Annual Work Unit. 1. Deviations from sample means (=0), z-scores based, scaled values
Source: Estimations.

Table B.2. French crop farms: Performance classes

Descriptive statistics and estimates, 1989 to 2016

	Performance class 4 Most productive (phase I class 4, 11.6%)	Performance class 3 Medium productive I (phase I class 1, 55.4%)	Performance class 2 Medium productive II (phase I class 3, 8.5%)	Performance class 1 Least productive (phase I class 2, 24.6%)
Performance				
Estimated values				
Productivity level (Euro)	162 999***	147 931***	142 130***	58 029***
Technical Change (% p.a.)	-2.431***	1.242***	0.769***	-2.394***
Characteristics				
Deviations from Standardised Sample Means[1]				
Farm structure (index 01)				
Family/hired labour ratio	0.1699	-0.0047	0.0383	-0.0827
Land endowment (ha)	0.7770	0.1826	-0.7904	-0.5038
Form of ownership (1-family farms, 2-partnerships, 3-other)	0.1612	0.1103	-0.1640	-0.2677
Environmental sustainability (index 02)				
Chemicals use (EUR per ha)	0.1028	-0.0228	0.5971	-0.2038
Organic production (1=yes, 0=no)	0.0410	0.0268	-0.1012	-0.0446
Fuel per ha (EUR per ha)	0.0375	-0.0125	0.0662	-0.0123
Environmental subsidies per ha (EUR per ha)	0.1167	0.0247	-0.1450	-0.0605
Tillage area (ha)	0.7503	0.1875	-0.7912	-0.5019
Innovation-commercialisation (index 03)				
Net investment ratio (per total assets)	-0.2424	0.2318	0.1959	-0.4760
Share contract farming	-0.0103	-0.0079	0.1339	-0.0237
Share land rented	0.3467	0.1712	-0.0575	-0.5292
Biofuel income (EUR)	0.2119	0.0443	-0.1462	-0.1490
Miscellaneous income (EUR)	0.1890	0.0986	0.1861	-0.3756
Insurance expenses (EUR)	0.7515	0.1493	-0.1779	-0.6287
Technology (index 04)				
Capital / labour ratio (EUR per AWU)	-0.4015	0.2974	-0.2432	-0.3969
Labour per ha (AWU per ha)	-0.1803	-0.1336	1.3781	-0.0912
Capital per ha (EUR per ha)	-0.3383	-0.0016	1.0677	-0.2067
Materials per ha (EUR per ha)	-0.0585	-0.0475	0.5476	-0.0551
Diversity (index 05)				
Herfindahl Index (sqrt[Σ(yi/Y)2])	-0.0483	-0.0307	-0.5353	0.2773
Production diversity (yc/ΣY)	-0.1411	-0.0605	1.0496	-0.1606
Forest area (ha)	-0.0474	-0.0368	-0.0241	0.1136

	Performance class 4 Most productive (phase I class 4, 11.6%)	Performance class 3 Medium productive I (phase I class 1, 55.4%)	Performance class 2 Medium productive II (phase I class 3, 8.5%)	Performance class 1 Least productive (phase I class 2, 24.6%)
Individual (index 06)				
Age (years)	1.4519	-0.1584	-0.3049	-0.2213
Location (index 07)				
Subregion 1 nuts 2 FR10	0.0427	0.0932	-0.2150	-0.1557
Subregion 2 nuts 2 FR21	-0.0172	0.0643	-0.2874	-0.0372
Subregion 3 nuts 2 FR22	-0.1040	0.1198	-0.1114	-0.1824
Subregion 4 nuts 2 FR23	-0.0589	0.0466	0.0324	-0.0884
Subregion 5 nuts 2 FR24	0.0821	-0.0184	-0.2630	0.0939
Subregion 6 nuts 2 FR25	-0.0315	0.0353	-0.0615	-0.0434
Subregion 7 nuts 2 FR26	0.1898	-0.0446	-0.2188	0.0870
Subregion 8 nuts 2 FR30	-0.1822	0.0604	0.3712	-0.1789
Subregion 9 nuts 2 FR41	0.1726	0.0168	-0.1689	-0.0607
Subregion 10 nuts 2 FR42	-0.1205	0.0423	0.1812	-0.1013
Subregion 11 nuts 2 FR43	0.0331	-0.0157	-0.0323	0.0311
Subregion 12 nuts 2 FR51	0.0422	-0.0433	0.0839	0.0486
Subregion 13 nuts 2 FR52	-0.0270	-0.0085	0.1703	-0.0270
Subregion 14 nuts 2 FR53	0.0791	-0.0413	-0.0982	0.0897
Subregion 15 nuts 2 FR61	-0.0353	-0.0317	0.1251	0.0447
Subregion 16 nuts 2 FR62	-0.1109	-0.0762	0.9295	-0.0979
Subregion 17 nuts 2 FR63	0.0509	-0.0634	-0.1549	0.1725
Subregion 18 nuts 2 FR71	-0.0911	-0.0662	0.6240	-0.0241
Subregion 19 nuts 2 FR72	0.0301	-0.1219	-0.2070	0.3321
Subregion 20 nuts 2 FR81	-0.0045	-0.0208	0.0126	0.0447
Subregion 21 nuts 2 FR82	-0.0032	-0.0378	0.0122	0.0825
Subregion 22 nuts 2 FR83	0.0588	-0.0159	-0.1238	0.0510
Subregion 23 nuts 2 FR91	-0.0284	-0.0071	0.0775	0.0026
Subregion 24 nuts 2 FR92	-0.0388	-0.0303	0.1392	-0.0349
Subregion 25 nuts 2 FR94	-0.0329	0.0038	0.1008	-0.0281
Subregion 26 nuts 2 FRA1	0.1356	-0.0278	0.0160	-0.0067
Subregion 27 nuts 2 FRA2	0.0479	-0.0164	0.0990	-0.0199
Subregion 28 nuts 2 FRA3	0.0787	-0.0133	0.1087	-0.0446
(all: 1=yes, 0=no)				
Altitude (1- <300m, 2- 300-600m, 3- >600m)	0.1620	-0.1004	-0.0999	0.1846
Less favoured area payments (EUR)	-0.4843	-0.0531	-0.0637	0.3697
Household (index 08)				
Off-farm income share	-0.0352	-0.0673	-0.0687	0.1919
Rural support (EUR)	0.4211	-0.0154	-0.1432	-0.1141
Financial (index 09)				
Total assets (EUR)	0.2023	0.2226	-0.0665	-0.5737
Total subsidies (EUR)	-0.6007	0.2120	-0.0942	-0.1623
Equity/debt ratio	0.0556	-0.0082	-0.0083	-0.0048

Notes: AWU: Annual Work Unit. 1. Deviations from sample means (=0), z-scores based, scaled values.
Source: Estimated values (project phase I).

Table B.3. Italian crop farms: Performance classes

Descriptive statistics and estimates (2008 to 2015)

	Performance class 3 Most productive (phase I class 1, 51.5%)	Performance class 2 Medium productive (phase I class 3, 41.5%)	Performance class 1 Least productive (phase I class 2, 7%)
Performance			
Estimated Values			
Productivity level (Euro)	46 102***	27 266***	16 654***
Technical change (% p.a.)	-0.675***	1.501***	1.779***
Characteristics			
Deviations from Standardised Sample Means[1]			
Farm structure (index 01)			
Family/hired labour ratio	-0.1698	0.1672	0.2696
Land endowment (ha)	0.0287	-0.0242	-0.0714
Form ownership: (1-self-employment, 2-legal person, 3-cooperative form)	0.0839	-0.0715	-0.2041
Environmental sustainability (index 02)			
Chemicals use (EUR per ha)	0.1152	-0.1543	0.0732
Organic (probability)	0.0811	-0.0833	-0.1071
Environmental subsidies (EUR per ha)	0.0259	-0.0365	0.0277
Innovation-commercialisation (index 03)			
Net investment ratio (per total assets)	0.0007	-0.0051	0.0263
Share land rented	0.1783	-0.1542	-0.4169
Cooperation (probability)	0.0469	-0.0478	-0.0641
Irrigated area ratio	0.1956	-0.1663	-0.4756
Agritourism (probability)	-0.1055	0.0761	0.3419
Technology (index 04)			
Capital / labour ratio (EUR per hour)	0.0459	-0.0648	0.0495
Capital per ha (EUR per ha)	0.0534	-0.0827	0.1047
Materials per ha (hour per ha)	0.1158	-0.1446	0.0083
Total assets (EUR)	0.0005	-0.0036	0.0189
Diversity (index 05)			
Herfindahl Index (sqrt[Σ(yi/Y)2])	0.5234	-0.5244	-0.7752
Production diversity (yc/ΣY)	0.5285	-0.4559	-1.2447
Forestry (probability)	-0.0626	0.0243	0.3334
Individual (index 06)			
Age (years)	-0.1401	0.1699	0.0221
Education (1:primary, 2: secondary, 3: high, 4: college 1st, 5: college 2nd)	0.0688	-0.0955	0.0648
Gender (1-male, 0-female)	0.0122	0.0131	-0.1770
Location (index 07)			
Less Favoured Area (1 not to- 3 severely disadvantaged)	0.0831	-0.1401	0.2331
Altitude (1: <300m, 2: 300-600m, 3: >600m)	0.0716	-0.1324	0.2747

Notes: AWU: Annual Work Unit. 1. Deviations from sample means (=0), z-scores based, scaled values.
Source: Estimated values (project phase I).

Table B.4. UK crop farms: Performance classes

Descriptive statistics and estimates, 1995 to 2017

	Performance class 3 Most productive (phase I class 1, 49.1%)	Performance class 2 Medium productive (phase I class 2, 8%)	Performance class 1 Least productive (phase I class 3, 42.9%)
Performance			
Estimated values			
Productivity level (Euro)	241 702***	205 704***	118 929***
Technical change (% p.a.)	1.114***	3.271***	-2.394***
Characteristics			
Deviations from standardised sample means[1]			
Farm structure (index 01)			
Family/hired labour ratio	0.0148	-0.0712	-0.0037
Number of holdings	0.1012	-0.1107	-0.0951
Land (ha)	0.1025	-0.3494	-0.0523
Form of ownership	0.0216	-0.0742	-0.0109
Environmental sustainability (index 02)			
Chemicals use (GBP per ha)	0.2629	0.8822	-0.4643
Organic production share	0.0774	0.1140	-0.1097
Fuel per LU (GBP per LU)	0.0402	1.2536	-0.2787
Environmental subsidies per ha (GBP per ha)	0.2539	-0.0659	-0.2780
Tillage area (ha)	0.0604	-0.3186	-0.0098
Innovation-commercialisation (index 03)			
Net investment ratio (per total assets)	0.0819	0.1345	-0.1186
Share contract farming	0.0244	0.0406	-0.0362
Share land rented	0.0147	0.0916	-0.0338
Biofuel income (GBP)	0.0439	0.0127	-0.0526
Technology (index 04)			
Capital / labour ratio (GBP per AWU)	0.0397	-0.0172	-0.0421
Material per land (GBP per ha)	0.0449	0.3299	-0.1126
Labour per land (AWU per ha)	-0.1448	1.3945	-0.0934
Capital per land (GBP per ha)	-0.0013	1.4336	-0.2647
Diversity (index 05)			
Herfindahl Index (sqrt[Σ(yi/Y)2])	-0.4399	0.4495	0.4194
Production diversity (yc/ΣY)	-0.3854	0.1558	0.4116
Woodland area (ha)	-0.0138	-0.0847	0.0315
Individual (index 06)			
Age (years)	0.0270	-0.0138	-0.0283
Gender (1-female, 2-male)	0.7555	0.1771	-0.8965
Education	0.5774	0.0608	-0.6712
(0 School only 1 GCSE or equivalent 2 A level or equivalent 3 College / National Diploma/ certificate 4 Degree 5 Postgraduate qualification 6 Apprenticeship 9 Other)			
Location (index 07): ten subregions			
(all: 1=yes, 0=no)			
Altitude	0.8156	0.1681	-0.9635
(1 Most of holding below 300m 2 Most of holding at 300m to 600m 3 Most of holding at 600m or over 4 Data not available)			
Less favoured area	0.0195	0.0335	-0.0285

	Performance class 3 Most productive (phase I class 1, 49.1%)	Performance class 2 Medium productive (phase I class 2, 8%)	Performance class 1 Least productive (phase I class 3, 42.9%)
(1 All land outside LFA 2 All land inside SDA 3 All land inside DA 4 50% + in LFA of which 50% + in SDA 5 50% + in LFA of which 50% + in DA 6 <50% in LFA of which 50% + in SDA 7 <50% in LFA of which 50% + in DA)			
Rural-urban classification	0.8026	0.1433	-0.9441
(1 Urban > 10k – sparse 2 Town and fringe – sparse 3 Village - sparse 4 Hamlet and isolated dwellings - sparse 5 Urban > 10k – less sparse 6 Town and fringe – less sparse 7 Village – less sparse 8 Hamlet and isolated dwellings – less sparse)			
Household (index 08)			
Off-farm income share	-0.1338	0.2905	0.0990
Labour spouse (AWU)	0.0674	0.1127	-0.0979
Financial (index 09)			
Total assets (GBP)	0.2574	-0.0961	-0.2764
Total subsidies (GBP)	-0.0483	-0.0510	0.0644
Equity/debt ratio	0.0754	-0.2137	-0.0566
Total assets (GBP)	0.2574	-0.0961	-0.2764

Notes: AWU: Annual Work Unit. 1. Deviations from sample means (=0), z-scores based, scaled values.
Source: Estimated values (project phase I).

Table B.5. Czech dairy farms: Performance Classes

Descriptive statistics and estimates (2005 to 2015)

	Performance class 3 Most productive (phase I class 1, 33.9%)	Performance class 2 Medium productive (phase I class 3, 32.5%)	Performance class 1 Least productive (phase I class 2, 33.6%)
Performance			
Estimated values			
Productivity level (Euro)	740 489***	121 463***	60 892***
Technical change (% p.a.)	2.062***	0.366***	0.968***
Characteristics			
Deviations from Standardised Sample Means[1]			
Farm structure (index 01)			
Family/hired labour ratio	-0.2094	-0.0952	0.3031
Herd size (LU)	0.9596	-0.2041	-0.7711
Land (ha)	0.8898	-0.0860	-0.8147
Form of ownership (1-self-employment, 2-legal person, 3-cooperative)	0.8975	0.0022	-0.9075
Environmental sustainability (index 02)			
Stocking density (LU per ha)	-0.1833	-0.3750	0.5466
Chemicals use (EUR per ha)	0.6963	-0.2225	-0.4878
Organic (probability)	-0.2018	0.2034	0.0074
Environmental subsidies (EUR per ha)	0.2933	0.2883	-0.5740
Innovation-commercialisation (index 03)			
Net investment ratio (per total assets)	0.3282	-0.1347	-0.2011
Share land rented	0.6768	-0.0705	-0.6148
Biofuel Income (EUR)	0.3300	-0.1452	-0.1928
Technology (index 04)			
Capital / labour ratio (EUR per hour)	-0.0768	-0.1241	0.1972
Capital per cow (EUR per LU)	0.0282	-0.1361	0.1029
Labour per cow (AWU per LU)	0.0921	0.2656	-0.3492
Total assets (EUR)	0.8588	-0.2256	-0.6487
Diversity (index 05)			
Herfindahl Index (sqrt[Σ(yi/Y)2])	-0.1083	-0.6264	0.7135
Production diversity (yc/ΣY)	-0.0020	-0.7632	0.7506
Individual (index 06)			
Age (years)	0.2623	0.0023	-0.2669
Location (index 07)			
Less Favoured Area payments (EUR)	0.4644	0.2244	-0.6849
Altitude (1- <300m, 2- 300-600m, 3- >600m)	-0.0822	0.3633	-0.2676

Note: LU: Livestock Unit. AWU: Annual Work Unit. 1. Deviations from sample means (=0), z-scores based, scaled values.
Source: Estimations.

Table B.6. Danish dairy farms: Performance classes

Descriptive statistics and estimates, 2010 to 2016

	Performance class 3 Most productive (phase I class 1, 66.9%)	Performance class 2 Medium productive (phase I class 2, 15.9%)	Performance class 1 Least productive (phase I class 3, 17.2%)
Performance			
Estimated values			
Productivity level (Euro)	695 809***	655 091***	367 261***
Technical change (% p.a.)	1.780***	2.969***	2.020***
Characteristics			
Deviations from standardised sample means[1]			
Farm structure (index 01)			
Family/hired labour ratio	-0.0903	0.0099	0.3448
Herd size (LU)	0.1169	-0.1887	-0.2817
Land (ha)	0.0379	0.2605	-0.3925
Environmental sustainability (index 02)			
Stocking density (LU per ha)	0.0044	-0.1096	0.0855
Chemicals use (EUR per ha)	0.1754	-0.2492	-0.4544
Organic (probability)	-0.2062	1.0849	-0.2069
Environmental subsidies (EUR per ha)	-0.1032	0.5558	-0.1158
Innovation-commercialisation (index 03)			
Net investment ratio (per total assets)	-0.0172	0.1436	-0.0671
Share land rented	0.0759	0.0632	-0.3567
Contract farming (prob)	0.0339	-0.0061	-0.1276
Technology (index 04)			
Capital / labour ratio (EUR per AWU)	-0.0565	0.4872	-0.2345
Capital per cow (EUR per LU)	-0.0481	0.3123	-0.1036
Fodder per cow (EUR per LU)	-0.0146	0.0799	-0.0176
Milking system (1-pipes, 2-carousel, 3-AMS, 4-milking parlour, 5-others)	0.0012	0.3592	-0.3409
Diversity			
Herfindahl Index (sqrt[Σ(yi/Y)2])	-0.1555	-0.9565	1.5046
Individual			
Age (years)	-0.0318	0.0021	0.1228
Farming experience (years)	-0.0091	-0.0393	0.0726
Location			
Municipality (various)	0.0144	-0.0305	-0.0281
Household			
Off-farm income (EUR)	-0.0292	0.1931	-0.0663
Financial			
Total assets (EUR)	0.0131	0.2892	-0.3217
Total subsidies (EUR)	0.0749	0.3819	-0.6509
Equity/debt ratio	-0.0257	-0.0261	0.1212

Note: LU: Livestock Unit. AWU: Annual Work Unit.
1. Deviations from sample means (=0), z-scores based, scaled values.
Source: Estimations.

Table B.7. Norwegian dairy farms: Performance classes

Descriptive statistics and estimates (2005 to 2016)

	Performance class 3 Most productive (phase I class 1, 64.6%)	Performance class 2 Medium productive (phase I class 3, 19.2%)	Performance class 1 Least productive (phase I class 2, 16.2%)
Performance			
Estimated values			
Productivity level (Euro)	84 379***	79 705***	39 383***
Technical change (% p.a.)	2.521***	0.493***	-0.412***
Characteristics			
Deviations from Standardised Sample Means[1]			
Farm structure (index 01)			
Family/hired labour ratio	-0.0018	-0.1255	0.1554
Herd size (LU)	0.0286	0.2536	-0.4126
Land (ha)	-0.1056	0.4117	-0.0661
Environmental sustainability (index 02)			
Stocking density (LU per ha)	0.1841	-0.2452	-0.4419
Chemicals use (EUR per ha)	0.2390	-0.5829	-0.2619
Organic (probability)	-0.2023	0.7492	-0.0801
Environmental subsidies (EUR per ha)	-0.1086	0.3365	0.0344
Innovation-commercialisation (index 03)			
Net investment ratio (per total assets)	0.0079	-0.0294	0.0032
Share land rented	-0.0546	0.0617	0.1441
Contract farming (prob)	-0.0136	-0.0933	0.1641
Technology (index 04)			
Capital / labour ratio (EUR per hour)	-0.0647	0.2559	-0.0449
Capital per cow (EUR per LU)	-0.0458	0.0476	0.1231
Fodder per cow (EUR per LU)	0.0967	-0.2599	-0.0777
Diversity (index 05)			
Herfindahl Index (sqrt[Σ(yi/Y)2])	0.3187	-0.0395	-1.2194
Individual (index 06)			
Age (years)	-0.0076	0.0134	0.0143
Gender (0-male, 1-female)	-0.0479	0.0041	0.1857
Location (index 07)			
Dairy zone (0-10, increasingly disadvantaged)	0.1245	-0.5065	0.1031
Forest income (EUR)	-0.1403	0.5377	-0.0768
Household (index 08)			
Female/male labour ratio	-0.0461	0.0502	0.1238
Off-farm income (EUR)	-0.2385	0.5358	0.3154
Financial (index 09)			
Total assets (EUR)	-0.0198	0.2811	-0.2412
Total subsidies (EUR)	-0.0822	0.3335	-0.0670

Note: LU: Livestock Unit. AWU: Annual Work Unit. 1. Deviations from sample means (=0), z-scores based, scaled values.
Source: Estimations.

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This report was declassified by the Working Party on Agricultural Policies and Markets in June 2021 and was prepared for publication by the OECD Secretariat and was prepared for publication by the OECD Secretariat.

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