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One or many European models of agriculture? How heterogeneity influences income creation among farms in the European Union

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Abstract: Agricultural structures are quite heterogeneous across the European Union (EU), and it is likely that the underlying technology also differs across regions. In this article, we claim that the heterogeneity of agriculture across the EU affects the process of income creation (i.e. the relative importance of the factors of farm income differ for different agricultural models). A panel of farms representative for 125 regions reporting to the EU Farm Accountancy Data Network (FADN) during the period from 2007 to 2018 is used. In this article, those regions are grouped into three clusters. A system generalised method of moments (GMM) panel estimator is applied to each cluster. The results showed that total factor productivity (TFP), relative prices and agricultural subsidies make different contributions to farm net value added (FNVA). In particular, the income growth of farms in regions dominated by large farms seems to react more to marginal changes of the explanatory variables.

Keywords: cluster analysis; dynamic panel models; Färe-Primont index; farm income; total factor productivity

A major concern of the post-2020 Common Agricultural Policy (CAP) proposal was to make it more flexible to provide better coherence between its general objectives and the needs of specific member states (European Commission 2017). This is because the agricultural sector across the European Union (EU) is highly diversified, despite the existence of the so-called European model of agriculture. However, its objectives are rather vague. According to the European model of agriculture, agriculture should be economically competitive and at the same time contribute to the improvement of living standards in rural areas without placing a burden on the environment (Cardwell 2004).

Specific features of European agriculture in comparison with that in other developed regions of the world include a large share of own and family labour input, a low level of concentration and a low scale of production. However, one of the most characteristic features of the agricultural sector across the EU is its strong heterogeneity, manifested in the coexistence of modern and traditional agriculture (Sortino and Chang Ting Fa 2009).

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That persisting heterogeneity has been the reason for studies aimed at allocating spatially specific types of agriculture to European countries or regions (Kempen et al. 2011). However, in their fundamental works, Hayami and Ruttan (1970) and Kostrowicki (1982) claim that the resource relations resulting from relative prices of individual inputs seem to be particularly important in forming the dominant agricultural model or type. In addition, the agrarian structure and relations between the factors of production may result from both, historical backgrounds and current policy (Jepsen et al. 2015). This situation seems still to be true for contemporary Europe. For example, in areas with low population density (e.g. central Spain), agriculture is more extensive, whereas in areas where land is particularly valuable (e.g. the Netherlands), farming is usually much more intensive, and the land factor is replaced by capital inputs.

In this article, we claim that the heterogeneity of agriculture across the EU affects the process of income creation – that is, the importance of the factors of farm income differs across different agricultural models. There is a relatively rich body of literature on spatial income disparities in agriculture in EU countries and across regions (Elsholz and Harsche 2014; Hill and Bradley 2015). However, to our knowledge, there is a lack of research to analyse the differences in the determinants of farm income systematically across the EU's different agricultural systems.

According to microeconomic theory, farm income or profit is determined mainly by two factors: price effects [terms of trade (ToT)] and quantity effects (Grifell-Tatjé and Lovell 1999). In other words, one may say that an increase in farm income depends on the change in total factor productivity (TFP) and the change in ToT. The change in TFP can undergo decomposition into technical efficiency change, technological change (TC) and scale efficiency change. TFP is, therefore, an indicator of a farmer's efforts and exogenous technological progress. ToT is an exogenous market factor, given that we assume that a single farmer has no influence on market prices.

However, as noted by Kroupova (2016) in the context of the EU, farm income or profit is further affected by the subsidies in the CAP. Despite several studies on capitalisation of direct payments in land prices (Kirwan and Roberts 2016), the marginal effect of policy instruments on the level of farm income is still unclear.

In this analysis, we assume that the effect of TFP on income growth will be more important in more traditional farming systems than in other farming systems because the former farms start from a lower level of productivity. In large-scale farming, the role of ToT should increase, as these farms are expected to be more integrated in output as well as input markets. In modern agriculture, the effect of subsidies on income growth may be especially important (compared with that in other agricultural systems), given that there is less room for income to grow by improving productivity.

Against this background, this study aims to analyse the contribution of CAP farm subsidies on the growth of farm income for different farm structures. To verify our hypotheses, we first ran a cluster analysis to map the agricultural heterogeneity of the EU Farm Accountancy Data Network (FADN) regions during the period from 2007 to 2018. Second, we calculated TFP indexes by using the Färe-Primont index. In the third step, we calculated the farm income model [farm net value added (FNVA) per annual work unit (AWU)] by using the system generalised method of moments (GMM) panel models. In these models, we treated TFP, ToT and subsidies as explanatory variables.

Our contribution to the existing literature is threefold. First, we proposed a new comprehensive classification of FADN regions on the basis of economic criteria, which may be applied in other studies. Second, we calculated the TFP development for EU regions, taking into account that different models of agriculture exist. Third, we showed that under different agricultural models, there are different paths of income growth. Our results provide information for policymakers in developing more effective policy instruments.

MATERIAL AND METHODS

Income definition. The FADN approach provides several variables to represent approximations of farm income. The most important ones are gross value added (called 'gross income' in the FADN terminology), FNVA and farm net income. As stated in the FADN database, on the basis of FNVA, holdings can be compared irrespective of the family/non-family nature of the factors of production employed. As we focus on all types of farms in this analysis, FNVA has been selected as the most appropriate approximation of farm income. FNVA is defined as gross farm income minus depreciation. Farm net income is FNVA minus total external factor costs plus balance subsidies and taxes on investments. The farm net income indicator may therefore overestimate the risk level, because it is sensitive to the level of use of non-family production inputs.

Clustering. As mentioned, European agriculture is quite heterogeneous. However, several structural

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characteristics such as farm size, the share of rented land or share of hired labour are similar in geographically proximate places. Therefore, a clustering approach reduces the influence of unobserved regional characteristics on the variables of interest, and it allows researchers to identify groups or sub-samples from the total sample. The clusters for representative farms in the FADN regions have been recently designated by Czyżewski et al. (2018) and Guth and Smędzik-Ambroży (2019). In the first of these studies, the clusters are determined based on the uptake of different types of subsidies. In the second study, clustering is based on production factor resources of representative farms.

Despite earlier efforts to cluster FADN regions, in this study, we propose a comprehensive classification to map structural heterogeneity across the EU. Our classification, inspired by the fundamental work of Hayami and Ruttan (1970) and Kostrowicki (1982), is based on the relations of basic resources. The three ratios are land to labour (a proxy for farm size), working capital (intermediate consumption) to land (a proxy for intensification), and fixed assets (excluding land) to labour (a proxy for technical equipment of work).

The following analysis makes use of FADN data covering the period from 2007 to 2018 (i.e. starting with the first year of the EU 2007–2013 financial perspective when Romania and Bulgaria joined the EU up to the most recent data available). To map the heterogeneity of European farm types and characteristics appropriately, we first grouped into clusters the 125 FADN regions of 26 EU member states (including the United Kingdom but excluding French overseas territories, the Canary Islands, and Croatia, which joined the EU in 2013). Because of data gaps, the Estonia and București-Ilfov regions were also excluded. The resulting clusters share similar levels of resource relations. The identification of clusters relies on Ward's method with Euclidean distances, which is an effective approach for running a cluster analysis.

We identified three basic resource relations that are used for deriving clusters:

- Fixed assets (FADN code SE441)/labour (SE011) (EUR/h): reflects capital intensity in relation to labour;
- Intermediate consumption (SE275)/land (SE025) (EUR/ha): a proxy of the level of intensification in agriculture;
- Land (SE025)/labour (SE011) (ha/h): a proxy of farm size.

For each farm representative for a given FADN region, the average values of these relations were calculated. Fixed assets and intermediate consumption were expressed in EUR; therefore, these values should be deflated before being used in the analysis. According to Bojnec and Fertő (2013), fixed assets were deflated by the input price index for goods and services contributing to agricultural investment (input 2), and intermediate consumption was deflated by the agricultural input price index for goods and services currently consumed in agriculture (input 1). These two deflators have been taken from Eurostat (2021).

The crucial issue for the clustering procedure is to identify an optimal number of clusters determined by the underlying data. To this end, we applied the Calinski-Harabasz criterion to a pre-selected range between two and six clusters. More than six clusters would make our analysis too complicated, and comparisons between clusters would be unclear for the readers. The practical appropriateness of the clustering procedure may be further evaluated by testing the significance of differences between the mean levels of variables in the identified clusters. If there are more than two clusters, analysis of variance may be used or its non-parametric counterpart, the Kruskal-Wallis test, when the distribution of variables is not normal. Both tests should be accompanied by *post hoc* pair tests to study whether there are only 'general' differences between clusters or whether there is a significant difference in each pair. The results of the Kruskall-Wallis test and post hoc Dunn's pairwise comparison tests are provided in Table S1 in electronic supplementary material (ESM); for the ESM see the electronic version.

Measuring TFP. There are many techniques to calculate the change in TFP. However, in this analysis, we opted for the non-parametric Färe-Primont productivity index because it is considered to have several advantages over other measures of productivity (O'Donnell 2014; Khan et al. 2015; Baráth and Fertő 2017; Martinez Cillero and Thorne 2019). The Färe-Primont index satisfies transitivity and identity axioms, which makes it much more suitable for comparisons among entities and over time (O'Donnell 2014). Transitivity means that a direct comparison of two observations (e.g. farms or periods) gives the same estimate of TFP change as would an indirect comparison through a third observation. Satisfying the identity axiom implies that for constant output and input quantity indexes, the TFP index takes the value of 1 (O'Donnell 2012b). Other popular TFP measures, such as the Fisher, Hicks-Moorsteen-Bjurek, Laspeyres, Malmquist, Paasche, and Törnqvist indexes, fail to pass the transitivity test (Martinez Cillero and

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Thorne 2019). A further advantage of the Färe-Primont index is that, in contrast to the Lowe index (O'Donnell 2012b), it does not require a price vector.

Let $q_{it} \in \mathfrak{R}_+^J$ and $x_{it} \in \mathfrak{R}_+^K$ denote vectors of output and input quantities for farm i in period t. According to O'Donnell (2012b), the TFP of farm i in period t can be calculated as the ratio of aggregated outputs (output quantity index) over aggregated inputs (input quantity index): $TFP_{it} = Q(q_{it})/X(x_{it})$. It follows that a comparison of the TFP index of two different farms i and h in the two periods t and s can be expressed as follows (O'Donnell 2014):

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \frac{Q_{it} / X_{it}}{Q_{hs} / X_{hs}} = \frac{Q_{it} / Q_{hs}}{X_{it} / X_{hs}} = \frac{Q_{hs,it}}{X_{hs,it}} \tag{1}$$

where: TFP_{it} – TFP of farm i in the period t; TFP_{hs} – TFP of farm h in the period s; Q – vector of outputs; X – vector in inputs for a given farm in a given period.

In this context, TFP change is a measure of output growth divided by a measure of input growth. This index is 'multiplicatively complete' (O'Donnell 2012a). The Färe-Primont index uses the non-negative, non-decreasing and linearly homogeneous aggregator distance functions (Khan et al. 2015). The Färe-Primont index that measures the TFP of farm i in period t relative to the TFP of farm h in period s is as follows (O'Donnell 2014):

$$TFP_{hs,it} = \frac{D_O\left(x_0, q_{it}, t_0\right)}{D_O\left(x_0, q_{hs}, t_0\right)} \frac{D_I\left(x_{hs}, q_0, t_0\right)}{D_I\left(x_{it}, q_0, t_0\right)} \tag{2}$$

where: $D_O(x_0, q, t_0)$ and $D_I(x, q_0, t_0)$ – Shephard output and input distance functions, respectively, and they represent the production technology available in period t_0.

The Färe-Primont index, as a distance-based index, can be estimated using data envelopment analysis methodology.

The inter-farm difference as expressed by the Färe-Primont index can undergo decomposition into technological differences and measures of differences in efficiency. Formally, the relative TFP index can be written as follows:

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}}\right)\left(\frac{OSME_{it}}{OSME_{hs}}\right) \tag{3}$$

where: TFP_t^* / TFP_s^* – technical (technological) change (an approximation of the production frontier movement); OTE – output-oriented 'pure' technical efficiency; $OSME$ – output-oriented scale-mix efficiency. The latter accounts for productivity shortfalls related to diseconomies of scale for both scale and scope (O'Donnell 2014).

According to Bojnec and Fertő (2013), we used agricultural production (SE131) as output, and we used as inputs total labour in hours (SE011), total used agricultural area in hectares (SE025), intermediate consumption as a proxy of current capital spending (SE275) and fixed assets (SE441).

Farm income determinants. O'Donnell (2012b), Sipiläinen et al. (2014) and Mugera et al. (2016) studied farm profitability by using TFP (and/or its decomposition) and price relations (ToT). Kroupova (2016) extended the approach of Sipiläinen et al. (2014) and added a decoupled subsidies component. In our study, we analysed FNVA per AWU, as we assumed that farmers (especially in family farming, which predominates in the EU) maximise their own income rather than profitability. We claimed that farmers who, *ceteris paribus*, increase their productivity and benefit from a relatively higher increase of output prices compared with input prices should experience an increase in farm income. Furthermore, in the testing of the policy objective, farm subsidies should have a positive effect on farm incomes.

The relative price change (ToT) is calculated as the ratio of changes of average agricultural output prices to changes in average input prices. Subsidies are recorded in FADN as current subsidies (SE605) and investment support (SE406). As our main interest in this analysis is to compare the strength of the income change with the determinants change, we expressed all variables as ratios. We calculated income, subsidies and productivity change, dividing the values from period t by the values from period $t - 1$, whereas input and output prices needed for ToT were originally expressed in chain index (ratio) form in the Eurostat database (Eurostat 2021).

Finally, we assumed that the reaction of income growth on changes in right-hand side variables was not linear. For example, when productivity growth starts from a low level, income growth might be higher compared with those of farms already operating at high levels of productivity (Cochrane 1958; Czyżewski et al. 2019). Therefore, all variables were expressed in logarithmic form. As an additional benefit, this approach enabled direct comparison of coefficients and interpretation as elasticities. Therefore, the empirical model explained a natural logarithm of change of the income (FNVA per AWU) by natural logarithms of changes of TFP, ToT and total subsidies.

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Because we studied income change rather than the level of income, a dynamic panel model was estimated. We followed the econometric literature, which suggests the estimation of a system by using a two-step GMM model (Blundell and Bond 1998) with finite-sample corrected standard errors (Windmeijer 2005). In this dynamic panel model, we assumed that unobserved panel-level effects were correlated with the lags of the dependent variable (income per worker change). Therefore, we had to include a lagged dependent variable on the right-hand side of the equation, and our model took the final following form:

$$\ln\left(\frac{\frac{FNVA}{AWU}_{it}}{\frac{FNVA}{AWU}_{i,t-1}}\right) = \beta_0 + \beta_1 \ln\left(\frac{\frac{FNVA}{AWU}_{i,t-1}}{\frac{FNVA}{AWU}_{i,t-2}}\right) + \beta_2 \ln\left(\frac{TFP_{it}}{TFP_{i,t-1}}\right) + \beta_3 \ln\left(ToT_{it}\right) + \beta_4 \ln\left(\frac{subsidies_{it}}{subsidies_{i,t-1}}\right) + \nu_i + \varepsilon_{it} \tag{4}$$

where: *FNVA* – farm net value added; *AWU* – annual work unit; *subsidies* – current subsidies and investments support; ν_i – unobserved individual-level effect; ε_{it} – observation-specific error term; ToT_{it} – terms of trade calculated as:

$$\frac{Average\ agri\ output\ price_t / average\ agri\ output\ price_{t-1}}{Average\ agri\ input\ price_t / average\ agri\ input\ price_{t-1}}$$

However, Equation (4) was identified only when the lagged variable was instrumented by exogenous instruments. According to Mugera et al. (2016), we used the five lags of dependent variables as instruments. Technically, it would be possible to use all available lags as instruments, but then the number of instruments would be large in comparison with the number of observations. Under such circumstances, the validity of the instruments could not be tested reliably because the Hansen test can be greatly weakened by instrument proliferation, and in two-step estimation (which is more efficient), the Sargan test is not robust.

Furthermore, the GMM technique allowed us to divide explanatory variables into strictly exogenous and predetermined or endogenous ones (Roodman 2009). We assumed that the ToT variable was strictly exogenous because a single farmer has no effect on market prices of outputs or inputs and treats these as market information. Subsidies may also be treated as exogenous from the farmers' perspective, given that their level has been initially agreed in the process of the political negotiations among member states. Obviously, larger farms receive more subsidies. However, given the operationalisation of farm income per working unit, we assumed that the influence of the size of the farms had been reduced. TFP, however, may be predetermined because we assumed that the level of income may have a feedback effect on famers' efforts, so this feedback effect influences inter-farm differences in technical efficiency. Therefore, in the terminology of the GMM approach, we used TFP as a regressor and IV-style instrument for the equation in levels, and we included the two variables, ToT and subsidies, as both regressors and IV-style instruments in the levels and the transformed equation.

RESULTS AND DISCUSSION

Clustering results. The procedure outlined resulted in four clusters of FADN regions. The pseudo *F*-test statistics for four clusters was the highest at 91.25. However, one cluster consisted of only two regions (Malta and the Netherlands), which were identified as outliers, because in these two countries, the average level of intensification (total intermediate consumption per ha) was extremely high, EUR 9 039 and EUR 7 204, respectively, whereas the sample average was EUR 1 315. At the same time, the average farm size (measured by land in ha per labour unit) is rather small, and in Malta, this relation is the smallest in the EU. Finally, we excluded this cluster, so further analysis was conducted on three clusters. In Table 1, we provide descriptive statistics of the three resource relations for each cluster.

Cluster 1 consists of 49 regions. These are mostly in northwestern Europe, with some in northern Italy and other parts of the EU (Figure 1). This cluster is distinguished by a high level of intensification; the level of current capital spending per ha is clearly the highest. At the same time, farms in this cluster may be seen as middle-sized when it comes to agricultural area, and the level of fixed capital per labour also is moderate. The dominant model of farming in this cluster may be referred to as intensive. Cluster 2 consists of 51 regions. In this cluster, small farms predominate. The capital factor use (both current and fixed) is relatively scarce, and it is clearly the lowest among the clusters. In cluster 2, the extensive/traditional model of farming predominates. This cluster comprises most of the regions from the so-called new EU (EU 12), plus some regions from Mediterranean countries. In cluster 3,

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Table 1. Descriptive statistics of variables used for cluster analysis

Variable	Intensive (cluster 1)		Extensive/traditional (cluster 2)		Large-scale (cluster 3)	
	mean	SD	mean	SD	mean	SD
Fixed assets/labour (EUR/h)	39.865	15.615	13.023	5.993	71.258	27.701
Intermediate consumption/land (EUR/ha)	1 726.219	677.870	767.564	299.651	1 082.550	366.316
Land/labour (ha/h)	0.014	0.007	0.010	0.007	0.036	0.010
Number of FADN regions	49		51		25	

FADN – Farm Accountancy Data Network; all differences between means in clusters are statistically different from zero; Kruskall-Wallis test results are provided in Table S1 in the ESM (for the ESM see the electronic version)
Source: Own elaboration based on Farm Accountancy Data Network (FADN) (European Commission 2020)

large farms with substantial fixed capital predominate. At the same time, the use of intermediate consumption is not as big as in cluster 1. These farms are spread mostly in some regions of France, the northeastern part of Germany (i.e. part of the former German Democratic Republic) and also some regions in the United Kingdom (mainly Scotland and Wales), Denmark and Sweden. We will consider this cluster large-scale agriculture.

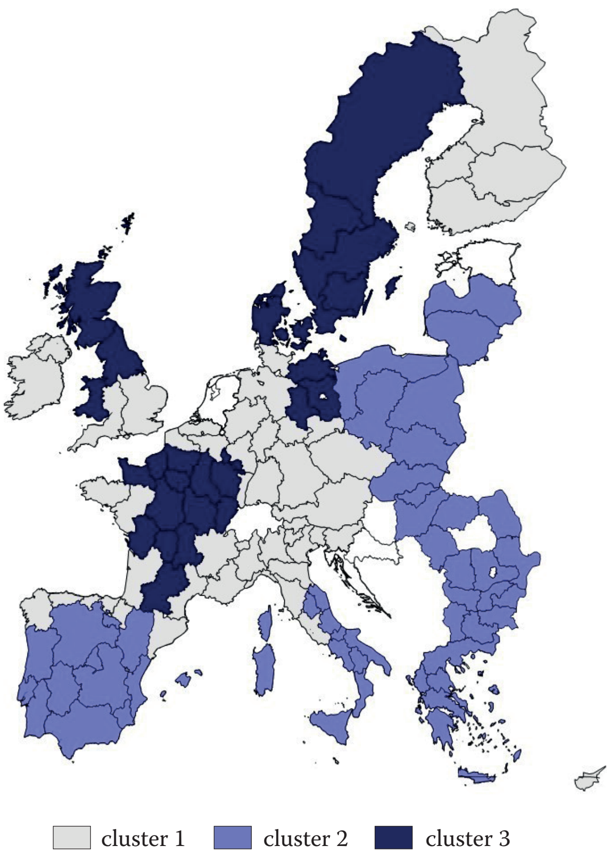

Figure 1. Main agricultural models across EU FADN regions

FADN – Farm Accountancy Data Network; cluster 1 – intensive farming; cluster 2 – extensive/traditional farming; cluster 3 – large-scale farming
Source: Own elaboration based on Farm Accountancy Data Network (FADN) (European Commission 2020)

The main message from the clustering exercise is similar to the ones provided by Giannakis and Bruggeman (2018). They used labour productivity at the Nomenclature of Territorial Units for Statistics 2 level to identify agricultural clusters across the EU. In brief, they found substantial differences between the northern and central regions and the continental peripheries (Mediterranean region, Eastern Europe), which constitute mainly (extensive/traditional) cluster 2 in our analysis.

Development of TFP. The Färe-Primont productivity index was calculated separately for each of the three clusters. This method could be seen as a simple version of the meta-frontier approach. In this framework, we assumed that, in practice, sample farms usually do not have equal access to technology, so separate frontiers should be calculated for the three groups. Otherwise, TFP change calculations would be biased, which is especially important in analysing a structure as heterogeneous as the EU (Cechura et al. 2017). In Table 2, we provide descriptive statistics of variables used in TFP calculations, and in Table 3 we present a decomposition of TFP change based on Equation (3) for each year and cluster. As expected, means of output and inputs differ across the three clusters. However, the differences were less than expected for the variable of labour. The mean number of working hours per year in extensive/traditional agriculture was smaller by only approximately 14% compared with that in the intensive farming cluster and by 20% compared with that in the large-scale farming cluster. However, the mean output levels were one-third the size and one-fifth the size, respectively. Thus, labour productivity must differ substantially across the three clusters.

Figure 2 and Table S2 (for Table S2 see the ESM; for the ESM see the electronic version) show an increase, on average, in TFP across all clusters during the study

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Table 2. Descriptive statistics of variables used in Färe-Primont TFP index calculations

Variable	Intensive (cluster 1)		Extensive/traditional (cluster 2)		Large-scale (cluster 3)	
	mean	SD	mean	SD	mean	SD
Output (EUR)	156 423	156 214	47 047	69 678	257 398	200 379
Labour (h)	4 320	3 177	3 731	3 164	4 632	3 657
Land (ha)	65.1	76.7	40.7	70.7	163.1	119.3
Intermediate consumption (EUR)	98 766	106 546	27 007	53 332	169 819	131 931
Fixed assets (EUR)	173 871	152 086	49 913	73 221	293 755	163 675
Number of observations	588		612		300	

TFP – total factor productivity

Source: Own elaboration based on Farm Accountancy Data Network (FADN) (European Commission 2020)

Table 3. Descriptive statistics of variables used for dynamic panel model estimations

Variable	Intensive (cluster 1)		Extensive/traditional (cluster 2)		Large-scale (cluster 3)	
	mean	SD	mean	SD	mean	SD
FNVA/AWU (EUR)	28 753	10 769	14 881	8 458	38 272	14 731
$(FNVA/AWU_{it})/(FNVA/AWU_{i,t-1})$	1.034	0.189	1.080	0.241	1.038	0.282
$TFP_{it}/TFP_{i,t-1}$	1.016	0.099	1.032	0.130	1.009	0.073
ToT_{it}	0.996	0.054	0.995	0.062	0.999	0.051
$Subsidies_{it}/subsidies_{i,t-1}$	1.031	0.159	1.096	0.280	1.003	0.070
Number of observations	539		561		275	

FNVA – farm net value added; *AWU* – annual work unit; *TFP* – total factor productivity; *ToT* – terms of trade

Source: Own elaboration based on Farm Accountancy Data Network (FADN) (European Commission 2020) and Eurostat (2021)

period. The main positive contributor to TFP growth for all three clusters was technical change. The role of technical efficiency, as well as scale and mix efficiency, differed substantially in the clusters.

The highest average pace of TFP growth occurred in the extensive/traditional farm cluster [3.2% *per annum* (p.a.) on average]. Given the lower capital intensity of agriculture in most of the regions in this cluster, this pattern supports the hypothesis of unconditional convergence. The average TFP in this cluster grew as much as 43% between 2007 and 2018. The main sources of TFP growth in this cluster were technical change and scale-mix efficiency change, whereas technical efficiency remained rather constant. The decomposition suggests that productivity growth in the cluster of extensive/traditional farms was driven more by the scale of production and the input-output mix (*OSME*).

Turning to the clusters of the intensive and large farms, results in Figure 2 and Table S2 (for Table S2 see the ESM; for the ESM see the electronic version) suggest that TFP growth was influenced mainly by technical change. It seems that both types of farms could access innovations that increase productivity. The comparatively low or even negative contribution of the change of technical efficiency, 0.4% per year for the intensive farm cluster and –0.3% per year for the large-farm cluster, suggests that these farms were already operating close to the frontier. Even more striking were the negative annual growth rates for the scale-mix efficiency change (*OSME*). In contrast to the traditional cluster, farms in both the intensive and large-farm clusters seemed to be less able to adjust their scale and output-input mix to changing market conditions.

Our results are in line with findings from other studies of European examples in which TC was the main contributor to TFP growth (Emvalomatis 2012; Keizer and Emvalomatis 2014; Marzec and Pisulewski 2019). Contradictory findings have been provided by Cechura et al. (2017), who found that TC among dairy farms in the new EU member states was negative (from 2004 to 2011), except for that in the Czech Republic and Slovakia.

Determinants of farm income. In the final step, we assessed the effect of TFP change, ToT and subsidy change on the change of FNVA per AWU. Table 3 pro-

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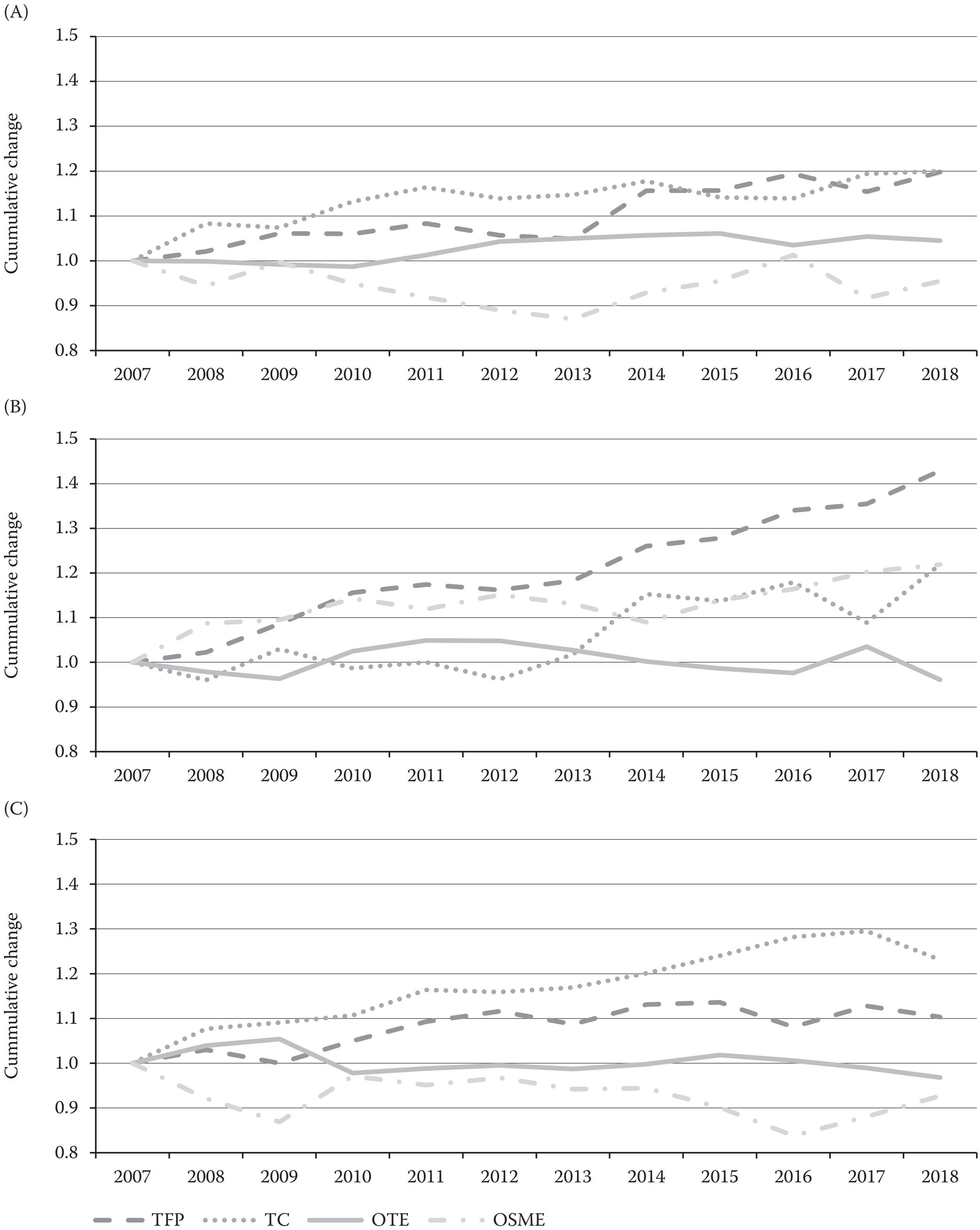

Figure 2. TFP development and its decomposition among identified clusters: (A) cluster 1 – intensive farming, (B) cluster 2 – extensive/traditional farming and (C) cluster 3 – large-scale farming

TFP – total factor productivity; TC – technical change; OTE – output-oriented technical efficiency; OSME – output-oriented scale mix efficiency

Source: Own elaboration based on Farm Accountancy Data Network (FADN) (European Commission 2020)

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vides descriptive statistics for the variables used, and the results of the estimations are presented in Table 4.

Mean values of our key variables of interest, as shown Table 3, range from EUR 14 881 per worker for the extensive/traditional farm cluster to EUR 38 272 per worker for the large-farm cluster. The average farm income per worker in the intensive cluster was closer to that of the large farms and accounted for EUR 28 753. The average pace of income growth among extensive/traditional farms was the highest, as the farms from the so-called new EU (which constitutes most of the cluster) experienced a high pace of income growth after EU accession. The subsidies were growing in every cluster, but because of the phasing-in mechanism in the EU 10, the pace of growth was the highest in the extensive/traditional cluster. On average, the development of output and input prices was unfavourable for farmers, but the effect was not large in quantitative terms.

Regarding the estimation results (Table 4), coefficients of all variables under consideration were statistically significantly different from zero, and their signs were consistent with the theory. The results of the Hansen test and the Arellano-Bond test for second-order correlation proved that the set of instruments was specified correctly.

The effect of TFP dynamics on income change differed among clusters. It was similar for the intensive and extensive/traditional cluster, but the TFP effect was clearly higher for the large-scale cluster. One reason could be comparatively low TFP dynamics in this cluster [Figure 2 and Table S2 (for Table S2 see the ESM; for the ESM see the electronic version)]. In other words, among large farms, there would be more potential for income growth based on productivity growth. A comparatively large positive and statistically significant effect of ToT on income change was identified for all clusters. Obviously, an increase in output prices relative to input prices benefits all farms. Our results are similar to those of Mugera et al. (2016) who found that ToT has a positive effect on profitability for a sample of US farms. However, in extensive/ traditional agricultural systems, the influence of ToT was lower than that for intensive and large-scale farming systems, which can be explained by the fact that farms in traditional farming systems are less integrated into markets (Borychowski et al. 2020). Large farms produce mostly for the market, so any change in ToT can significantly affect their income creation. Larger farms can benefit more from favourable market conditions for agriculture, but they are also more vulnerable to market risk.

Table 4. Determinants of farm income change

Variables	Intensive (cluster 1)	Extensive/traditional (cluster 2)	Large-scale (cluster 3)
FNVA/AWU_change (lag)	–0.127*** (0.025)	–0.087** (0.035)	–0.114*** (0.033)
TFP_change (Färe-Primont)	1.402*** (0.106)	1.427*** (0.087)	2.373** (0.221)
ToT_change	1.557*** (0.152)	1.326*** (0.108)	2.319*** (0.197)
Subsidies change	0.114*** (0.042)	0.176*** (0.035)	0.509** (0.192)
Constant	0.004 (0.003)	0.006 (0.005)	–0.010** (0.004)
AR2 test *P*-value	0.677	0.739	0.194
Hansen test *P*-value	0.330	0.503	0.207
Number of instruments	48	48	22
Observations	490	510	250
Number of regions	49	51	25

***,**, and *statistical significance at 0.01, 0.05, and 0.1, respectively; FNVA – farm net value added; AWU – annual work unit; TFP – total factor productivity; ToT – terms of trade; dependent variable: natural logarithm or farm net value added/AWU change; two-step sys-GMM dynamic panel model with robust standard errors

Source: Own elaboration based on Farm Accountancy Data Network (FADN) (European Commission 2020) and Eurostat (2021)

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Subsidy changes were a further positive driver of income change in all clusters. However, the marginal effect of subsidy growth was especially large among large farms. Because of degressivity (reduction of payments of more than EUR 150 000) or capping mechanisms introduced in some member states, the largest entities received smaller portions of subsidies than they would from a proportional distribution. Any increase in the level of subsidies has a relatively large effect on income. It is interesting that the marginal effect of subsidy change for the extensive/traditional model was only slightly higher than that for intensive farms, even though subsidies in the former grew on average much faster.

CONCLUSION

The aim of this research was to examine the responsiveness of farm income (FNVA) in relation to productivity, prices and subsidies. At the same time, we aimed at capturing the phenomenon of heterogeneous European agriculture by clustering EU FADN regions by using the relations of the factors of production and estimating separate dynamic panel models for three different clusters. Furthermore, we presented the decomposition of the change in TFP among the three main agricultural systems across the EU.

We have demonstrated that TFP has grown in all three identified agricultural systems in the EU during the period from 2007 to 2018, but the average pace of TFP growth in extensive/traditional agriculture was clearly higher than that in the other clusters. However, exogenous technical change was the main contributor to TFP growth in all clusters. Furthermore, in extensive/traditional farming, scale-mix efficiency also played an important role. Technical efficiency change, in turn, was negative in large-scale and extensive/traditional farming systems. It was positive only for the intensive cluster – and only slightly so.

Our analyses show that it is difficult to speak of a single universal model of European agriculture. Farms in Central and Eastern Europe and in some Mediterranean regions are rather small, and their capital saturation is rather low, as are the incomes per labour unit. However, these farms experienced the highest dynamics of productivity and subsidy growth. Although the sampled period covers two multi-annual financial frameworks of the EU and the Luxembourg reform, the level of subsidies per representative did not change much. Furthermore, evidence (Gocht et al. 2017) points to limited changes in farm management and production portfolios because of the newly introduced greening requirement. Therefore, we assume that the reform does not constitute a structural break within the panel data.

For all farms, the increases in productivity and ToT have been identified as the main contributors to income growth, *ceteris paribus*. Subsidy changes led to increased income, too, but the quantitative effect was much smaller. However, their marginal effect was approximately four times higher for large farms than for intensive farms and three times higher than for the extensive/traditional farming system.

On the basis of our results, it is possible to provide some policy recommendations. Large farms should focus on productivity gains, especially when it comes to scale-mix efficiency because the decrease in this component of productivity was particularly evident in the large-farm cluster. Farms belonging to the extensive/traditional cluster should concentrate on further TFP growth, mainly through the channel of technical efficiency, given that this factor was declining (on average) in the period studied. This finding is an important hint for agricultural policy, which should focus on strengthening farm advisory services that could help farmers to produce more efficiently.

Contrary to initial assumptions, changes in subsidies were not exceptionally important for income growth in intensive farming. The marginal effect of this variable was even stronger for large farms. This finding adds to the critical perspective on agricultural subsidies, which fail to reduce income differences across regions and between farms. Social policy goals would be better addressed by social policies targeting rural households in need.

We conclude that ToT is an important factor in explaining income growth among large farms. When price relationships become more favourable from the farm perspective, then large entities may benefit a lot. However, there is also a downside to this relationship. In periods when price relations become disadvantageous, these farms may experience particularly high losses. Our results may serve as evidence for the need to strengthen risk management tools as they are postulated in the current CAP reform. Large farms (but also intensive farms) may be especially interested in this kind of mechanism. Furthermore, intensified cooperation between farmers with respect to output as well as input markets could be a strategy to improve their ToT.

To obtain a more detailed picture that covers the heterogeneities within the FADN regions, farm-level data would be necessary. The application of our general framework to more specific problems can be considered as a promising line for further research.

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