

# Explaining farm structural change in the European agriculture: a novel analytical framework

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## Abstract

In this paper, we analyse the drivers of farm structural change in the EU-27, applying a novel analytical framework in the field of agricultural economics known as the multiplicative competitive interaction (MCI) model. MCI offers a more parsimonious specification for estimating models of regional farm group shares compared to the often-applied Markov approach. The MCI framework enables farm group-specific equations, which are used to account for drivers specific to certain farm groups. The MCI framework explains farm group shares at the regional level taken from the Farm Structure Survey (FSS) using socio-economic variables from the Farm Accountancy Data Network (FADN) and other databases for the period 1989–2013. We consider eight production specialisations and two size classes at the NUTS 2 regional level. The results indicate that the past farm structure explains approximately 36 per cent of the EU farm structure variation across regions and time, followed by natural conditions (16 per cent), agricultural prices (14 per cent), macroeconomic variables (9 per cent), subsidies (7 per cent), population (6 per cent) and agricultural income (6 per cent). Further, we have run a simulation experiment where we derived elasticities of structural change with respect to time-varying variables. The structural change appears to be the most elastic with respect to income and macroeconomic variables.

**Keywords:** farm structural change, MCI model, EU, FADN data, production specialisation, farm size

**JEL classification:** O13, Q18, O52

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## 1. Introduction

European Union (EU) agriculture has undergone significant structural changes over the last decades. The most evident and policy-relevant structural developments in EU agriculture are reflected in the declining number of farms, farm size growth and production re-specialisation over time. For example, the number of farms in the EU declined by an average of 3.7 per cent annually between 2005 and 2010. In contrast, average farm size expanded by 3.8 per cent per year in the same period. As farm size grows, farms tend to specialise in cereal cropping and grazing livestock and move away from permanent crops, granivores and mixed farming (European Commission, 2013b). Understanding the drivers of these past structural changes helps project future developments and has significant policy implications, as one of the key priorities of the Common Agricultural Policy (CAP) is to promote rural development (European Commission, 2013a) and prevent the abandonment of production in agricultural areas (European Commission, 2003).

The literature offers a multitude of determinants explaining farm structural change. However, a comprehensive theoretical framework accounting for all major drivers of structural adjustment in agriculture is not available. Important drivers identified include technology (economies of scale) (Cochrane, 1958) and productivity growth (Harrington and Reinsel, 1995), farm household and path dependency (Balmann *et al.*, 2006; Zimmermann and Heckelei, 2012), input and output prices and macroeconomic conditions (e.g. unemployment rate) (Zimmermann and Heckelei, 2012), regional characteristics, agricultural policies (Chau and de Gorter, 2005; Ben Arfa *et al.*, 2015) and competitive pressures from non-agricultural sectors for resources (Alvarez-Cuadrado and Poschke, 2009). Recent studies highlight the importance of farm interaction for strategic farm decisions due to the competition over land causing regional specific patterns and spatial dependencies (Storm, Mittenzwei and Heckelei, 2015b).

One key distinction between studies attempting to assess the drivers of structural change in agriculture is the use of either macro or micro data. Studies using macro-level data exploit information regarding farm structure (e.g. number of farms) at the regional or country level to explain its dynamics (entry and exit of farms) and drivers over time (Goetz and Debertin, 2001; Breustedt and Glauben, 2007). Meanwhile, studies based on micro data use farm-level information to explain farm structural change, typically with farm size growth models (Sumner and Leiby, 1987; Weiss, 1999; Bremmer *et al.*, 2004). For example, Röder *et al.* (2014) and Neuenfeldt *et al.* (2014) analyse the impact of various socio-economic drivers on changes in farm specialisation based on farm-level data. Recent studies also combine micro and macro data to make better use of the available information when identifying drivers and predicting farm structural change (Storm *et al.*, 2015a, 2016).

A second important distinction between studies is the methodological approach applied. One strand of literature applies various econometric tools (e.g. probit, panel data estimation) to explore a narrowly defined aspect of farm structural change, such as farm exit/entry choices, farm growth etc. (e.g.

Bremmer *et al.*, 2004; Foltz, 2004). Another strand of applications – the most widely used type – analyses structural change with a Markov transition probability model (e.g. Huettel and Margarian, 2009). Given the typically limited number of observations, the Markov model requires imposing some a priori assumptions on transitions between states to lower the number of parameters estimated, particularly when the number of farm sub-groups is large. Several studies use prior information or data combinations to overcome this ‘degrees-of freedom’ problem (Zepeda, 1995; Huettel and Jongeneel, 2011; Zimmermann and Heckelee, 2012; Storm *et al.*, 2015a, 2016).

The aim of this paper is to develop and apply a novel analytical framework in agricultural economics research – the multiplicative competitive interaction (MCI) model – to identify relevant determinants and their quantitative impact on farm structural change in EU-27 regions at the aggregated NUTS 2<sup>1</sup> level using information from the FSS and FADN for the period 1989–2013. We define farm structure by aggregated farm group shares at the regional level, which are specified by combining eight production specialisations (farm types) and two farm size classes into a total of 16 farm groups.

The proposed MCI empirical model relies on shares of aggregated farm groups of the farm population defined across EU regions. We calculate aggregated farm group shares at the NUTS 2 level from the FSS and calculate various variables derived from the FADN and other statistics to identify how farm group shares at the regional level are affected by farm characteristics, input and output prices, subsidies, macroeconomic variables and natural conditions. The MCI approach follows the theoretical framework underlying the market share attraction model from the marketing literature (Cooper and Nakanishi, 1988; Fok, Franses and Paap, 2002). The MCI approach allows us to capture and conveniently analyse farm structure development by regional shares of farm groups. This approach significantly reduces the parameter dimensionality problem encountered in the Markov approach: the disaggregated level of farm groups considered in this paper would result in many transitions (up to  $16 \times 16$ ) per region, causing significant parameter identification issues for the latter approach. Compared to the Markov approach, the MCI model reduces the number of parameters to be estimated but still allows for the identification of determinants of and prediction of farm group shares.

Our paper contributes to the existing literature on farm structural change in four ways. First, we propose a dynamic utility model – the MCI approach – as a novel analytical tool in this context. Second, the proposed analytical framework depicts farm structural change in terms of the development of regional farm group shares, but avoids the over-parameterisation problem of the Markov approach when micro data or prior information are not available.

1 ‘The NUTS classification subdivides the economic territory of the EU Member States into territorial units (regions) [...]. The classification is made up of three hierarchical levels: each Member State is divided into so-called NUTS 1 regions, which in turn are subdivided into NUTS 2 regions and then divided further into NUTS 3 regions’. (European Union, 2015: 4–5)

This increased parsimony of the model specification allows us to better identify the effect of various drivers on farm structural change represented by changes in farm group shares. Third, we estimate farm structural change alongside two dimensions (i.e. by farm specialisations and farm size), which to our knowledge, has only been done by Zimmermann and Heckelei (2012) with a Markov approach. Finally, we aim to identify the main drivers of farm structural change in the EU, assess their relative importance and derive corresponding elasticities of farm structural change. The scale and possibility of automation of the approach also opens up the possibility of incorporating farm structural change into ex-ante policy impact analysis linking at a larger scale, something often demanded but still rarely done in CAP assessments.

The remaining paper is structured as follows. The next section introduces the MCI approach, while Section 3 explains the construction of farm groups and the motivation of the set of explanatory variables. Section 4 presents the empirical model specification. Section 5 presents the results regarding the impact of determinants, explanatory contributions and elasticities of determinants. The final section presents the conclusions.

## 2. MCI model: the market share attraction approach

### 2.1. The market share approach in marketing research

Market share models were initially developed in marketing literature to explain the market shares of brands or products and investigate how they are affected by firms' own actions (e.g. marketing instruments and management choices), the actions of competitors and other factors such as general economic development or policy changes. This approach is also applied in the literature to other sectors like hospital services (Erickson and Finkler, 1985) and the financial sector (Banker and Kauffman, 1988; Banker *et al.*, 2010).

The most straightforward and prominent market share model is MCI, which analyses market shares in a competitive environment where the market is divided in  $M$  submarkets (e.g. brands, groups of customers, time periods or geographical regions). MCI models hypothesise that the determinant of market share is the attraction (or utility),  $U$ , that consumers feel towards alternative submarkets (e.g. brands) when making a purchasing choice given the available options. Following this consideration, the following relationship between the attraction (or utility) of submarket  $i$ ,  $U(i)$ , and its corresponding market shares,  $s(i)$ , can be derived:

$$s_i = \frac{U_i}{\sum_{j=1}^M U_j}; \quad \text{with} \quad \sum_{i=1}^M s_i = 1 \quad (1)$$

Equation (1) implies that the submarket that is most attractive (or with the highest utility) gains the largest market share. Another important implication of the formulation of equation (1) is that it brings competitive interaction into the model, which is provided by the normalisation in the denominator, which

sums attractions over all brands. The result is a competitive model because the submarket's  $i$  market share depends on the actions of other submarkets. In other words, the MCI model describes the method through which the market is split among competitors given the effort allocation of each of them (Bell, Keeney and Little, 1975; Kotler, 1984; Cooper and Nakanishi, 1988; Monahan and Sobel, 1990).

The MCI literature does not provide or claim a profit maximisation theory of the firms behind the MCI approach, as most profit maximisation models for a firm or group of firms impose unrealistic assumptions on share models, e.g. independence of irrelevant alternatives or non-satiety. Based on Cooper, the purpose of applying MCI is rather to reflect the forces driving rich competitive market interactions.<sup>2</sup>

## 2.2. Analysing farm structural change in the MCI context

We adopt the market share attraction framework developed in the marketing literature to estimate drivers for competitive structures in agriculture (Cooper and Nakanishi, 1988; Fok, Franses and Paap, 2002). More specifically, we apply the MCI approach to analyse farm structural change in the EU-27 for aggregated farm group shares distinguished by production specialisation and farm size. The farm group shares are calculated as the percentage of the number of farms belonging to a particular group in the total farm population. In contrast to our farm group share measure, market share is defined for a specific product/brand in the MCI formulation as represented in equation (1) – usually approximated by its sales volume in relation to total market sales (Cooper and Nakanishi, 1988). This difference between our group share measures and the MCI approach may pose inconsistencies for our estimation. We identify the following minimum set of assumptions regarding farmers' behaviour under which the MCI analytical framework given in equation (1) is consistent with our farm group shares representation in terms of farm population distribution:<sup>3</sup>

- i. Farm-level production programmes and decisions on structural investments are made by utility maximisation of the farm-household. The decision regarding the farmer's optimal production programme is made by incorporating all relevant information, such as output and input prices, subsidies, technological possibilities and other non-economic factors. We assume that the farm-household's utility maximisation depends on both the production of private goods (e.g. generation of farm income and long-term profitability) and the provision of environmental goods and services, as well as non-pecuniary benefits.

2 E-mail correspondence with Lee Cooper in 2017.

3 In Stokes (2006), another analytical framework – the Markov chain model – is also used to analyse farm structural change without explicitly relating the analytical framework to single farm behaviour. Instead, reasonable assumptions and conditions to link theory and methodology are derived.

- ii. A stratification of the farm population by production specialisation and size class encompasses groups with similar socio-economic and production characteristics. We assume that the resulting groups capture the production behaviour of all farms in the group.
- iii. Farm group shares, rather than the absolute number of farms belonging to a group, better reflect the distribution of groups at the regional level and enable comparability of farm structure between regions.
- iv. Market signals such as prices, subsidies and other relevant factors exist at the aggregated farm group level and are consistent with those that drive individual farmers' production choices and thus also determine the farm group shares.

The first assumption ensures that farmers' production decisions are consistent with the standard assumption of profit (or utility) maximisation usually considered in agricultural literature. The second assumption states that the individual farms belonging to a group are somehow homogenous. The third assumption normalises the farm groups in a region to allow comparability between regions. The last assumption requires that market signals at the farm group level are consistent with those that drive individual farmers' production choices. In other words, we assume that when a price, for example, signals individual farms to increase a specific production activity, it is likely that several individual farms in that farm group will change their production and hence their farm group classification. As a result, both the regional shares of the original farm group and the farm group to which the individual farms move change.

The theoretical justification of farm structural change in the MCI context would make it necessary to analytically relate farm group shares in the population to the distribution of farm production choices and show that this relationship is equivalent to the MCI model formulation in equation (1). However, such a derivation is not straightforward because the model formulation is highly discontinuous given that the classification of farms into specific groups is based on income thresholds at the farm level (i.e. it is based on income shares for the production specialisation classification and total farm income for the farm size classification). For this reason, we illustrate the consistency of the theoretical concept numerically using a simulation experiment for a synthetic farm population.

The numerical experiment assumes the profit maximisation of farms (see the GAMS code in Appendix A.4 in supplementary data at *ERA*E online). For each farm, production choice is simulated using an individual mathematical programming model that maximises individual farm profits. We run two experiments: one that considers 1,000 farms and a second one with 10,000 farms, to check the sensitivity of the results to the size of the farm population. The farm models are parameterised by randomly drawing prices, yields and land endowments for each farm. Subsequently, we run several price scenarios with a vector of price changes that result in different production choices by farmers in line with profit maximisation behaviour. We classify

**Table 1.** Coefficient of determination between the farm-level simulation model and the MCI approach

Farm group	For 1,000 farms	For 10,000 farms
Cereals	0.960	0.964
Sugar beet	0.912	0.972
Potatoes	0.996	0.999
Mixed	0.872	0.942
All together	0.969	0.988

farms by production specialisation into four farm groups using fixed income thresholds: cereal, sugar beet, potato and mixed farms. The number of farms in each group is divided by the total farm population to obtain the farm group shares.

We split the sample of simulated farms into a training set and a test set. We apply the MCI estimation to the training set using the aggregated farm group shares for the given prices. Finally, we compare both shares generated from the farm-level simulation model and those projected by the MCI model of the test set. The results are reported in Table 1, in which we show the coefficient of determination between the shares derived in the farm-level simulation model and the MCI approach. The high fit (greater than 87 per cent) shows that MCI is capable of reflecting/explaining the profit maximising behaviour of single farms well at the aggregated farm group level. The results are similar for both farm populations considered, although a higher population size slightly improves the fit between the farm-level simulation model and the MCI approach. These results confirm that our representation of farm group shares in terms of farm population distribution can be estimated with relatively high accuracy using the MCI approach as specified in equation (1).

### 2.3. The specification of the MCI framework for structural change

Following the market share attraction models applied in the marketing literature, three different model specifications can be identified: simple effects, differential effects and the fully extended model. The simple effects model assumes the same impact of a given explanatory variable on all market shares across all farm groups considered (e.g. the price of cereals has the same marginal impact on the share of dairy farms and cereal farms). The differential model allows the impact of explanatory variables to differ across farm groups' market shares (e.g. the price of cereals may have a different impact on dairy farm shares than cereal farm shares). In the fully extended model, the own- and cross-farm-group effects of explanatory variables may differ between farm group share equations. This approach permits analysing the impact of explanatory variables (e.g. age) observed in one farm group (e.g. cereal farms) on other farm group shares (e.g. dairy farms, permanent crop farms) (Cooper and Nakanishi, 1988; Gocht *et al.*, 2012).

In this paper, we employ the differential effect model. In line with equation (1), a farm group share in a region is defined by the aggregated utility generated from farming activities by farm group relative to the total utility obtained by all farm groups.

$$s_{i,t} = \frac{U_{i,t}}{\sum_{j=1}^M U_{j,t}} \quad (2)$$

where  $i$  and  $j$  are farm group indices,  $t$  is time,  $U_{i,t}$  is the utility of farm group  $i$  in  $t$ ,  $s_{i,t}$  is the share of farm group  $i$  in all farm groups in  $t$ ,  $M$  is the number of farm groups considered at the NUTS 2 level.

We assume that farm size and farm specialisation reflect different orientations in carrying out farming depending on different factors (explanatory variables), such as required investment strategies, policy measures, natural constraints or farm characteristics. Consider, for example, a region characterised by large cereal farms and small pig fattening farms. An increase in cereal price is expected to have a positive effect on large cereal farms and a negative one on small pig fattening farms. This means that the utility of large cereal farms increases relative to the utility of the pig fattening farms with increasing cereal prices. Consequently, and following equation (2), we observe an increase of the share of large cereal farms and a decrease of the share of small pig fattening farms. Note that the share of a farm group may decrease even when its utility increases if the absolute values of a farm group's utility changes less than for other farm groups (e.g. when cereal price increase has a greater positive effect on cereal farms than on mixed farms).

According to Cooper and Nakanishi (1988: 28), market share models must comply with two consistency requirements: (i) estimated market shares from the model are non-negative and (ii) they must add up to one. Two types of models fulfil these requirements: MCI and multinomial logit models. For this paper, we apply the MCI model, which formulates utility as a multiplicative function of explanatory variables:

$$U_{i,t} = e^{(\alpha_i)} \prod_{k=1}^K f_k(X_{k,i,t})^{\beta_{k,i}} \varepsilon_{i,t} \quad (3)$$

where  $K$  is the number of explanatory variables,  $X_{k,i,t}$  is the  $k$ th explanatory variable explaining the utility of farm group  $i$  in  $t$ ,  $\beta_{k,i}$  is the coefficient measuring the influence of the  $k$ th explanatory variable on the utility of farm group  $i$  in  $t$ ,  $\alpha_i$  is a farm group-specific parameter,  $f_k$  is the positive, monotone transformation of  $X_{k,i,t}$  and  $\varepsilon_{i,t}$  is the error term.

Nakanishi and Cooper (1982) and Cooper and Nakanishi (1988: 26–31, 108–110 and 128–130) have shown that one can estimate equations (2) and (3) by a dummy regression model defined by

$$\log(s_{i,t}) = \alpha_1 + \sum_{j=2}^M \alpha_j' d_j + \sum_{k=1}^K \sum_{j=1}^M \beta_{k,i} d_j \log(X_{k,i,t}) + \varepsilon_{i,t} \quad (4)$$

where  $i, j$  are farm group indices,  $d_j$  is a dummy variable for farm group  $j$  (with  $d_j = 1$  if  $j = i$  and 0 otherwise).<sup>4</sup>

After estimating equation (4), we calculate the shares of the farm groups using the normalisation procedure of the estimated dependent variable, as suggested by [Nakanishi and Cooper \(1982\)](#). That is, if we allow  $\hat{y}_{i,t}$  to be the estimate of the dependent variable in equation (4), the estimated farm group share,  $\hat{s}_{i,t}$ , is given as follows:

$$\hat{s}_{i,t} = \frac{\exp(\hat{y}_{i,t})}{\sum_{j=1}^M \exp(\hat{y}_{j,t})} \quad (5)$$

Farm group share  $i$  is calculated as the share of the inverse logarithm of the estimate divided by the sum of all the inverse logarithm estimates of the dependent variable over all farm groups.<sup>5</sup>

The subsequent normalisation renders it unnecessary to impose constraints on parameters ensuring that the shares add up to one. A further advantage is that farm group-specific sets of explanatory variables can be used to specify equation (4) for estimation. This advantage is particularly important in the presence of heterogeneous farm groups because different farm group shares may be affected by a variety of drivers. For example, coupled subsidies under the CAP are granted for selected production activities that are directly relevant for certain farm groups but not for others.

### 3. Data

#### 3.1. Construction of farm groups

We use the Farm Accountancy Data Network (FADN) typologies to construct farm groups. FADN is a European system of sample surveys conducted each year that collect detailed structural and accountancy data on EU farms. The FADN data are unique in the sense that it is the only source of harmonised and representative farm-level microeconomic data for the whole EU. Farms are selected to take part in the surveys on the basis of sampling frames established at the level of each region in the EU. The yearly FADN samples cover approximately 80,000 farms and approximately 90 per cent of the utilised agricultural land in the EU-27 ([European Commission, 2010](#)). The FADN data we employ in the paper cover the period 1989–2013.

The FADN classifies farms by production specialisation (principal type of farming) and farm size (economic size class). The number of farms in each

4 For a comprehensive derivation of this equation, see [Appendix A.1](#).

5 Note that the estimated dependent variable in this paper is the logarithm of the farm group share value. Consequently, we have to take the inverse of the logarithm of the estimated dependent variable before normalisation.

**Table 2.** Farm classification

Code	Name	Description
<i>Production specialisation types (TF)</i>		
TF1	Field crops	Specialist cereals, oilseed and protein crops; general field cropping (e.g. root crops, field vegetables)
TF2	Horticulture	Specialist market garden vegetables; specialist flowers and ornamentals; general market garden cropping
TF3	Permanents	Specialist vineyards; specialist fruit and citrus fruit; specialist olives; various permanent crops combined
TF4	Grazing livestock	Specialist dairying; specialist cattle-rearing and fattening; cattle-dairying, rearing and fattening combined; sheep, goats and other grazing livestock
TF5	Granivores	Specialist pigs, poultry, granivores combined
TF6	Mixed cropping	Mixed cropping (e.g. field crops and permanent crops, field crops and market gardening)
TF7	Mixed livestock	Mixed livestock, mainly grazing livestock; mixed livestock, mainly granivores
TF8	Mixed both	Field crops and grazing livestock combined; various crops and livestock combined
<i>Farm size class (ESG)</i>		
ESG8	Small farms	Farms with SO smaller than 250,000 Euros
ESG9	Large farms	Farms with SO greater than 250,000 Euros

typology is derived from the surveys of farm population available from the Farm Structure Survey (FSS). Each farm group in our paper is a combination of farm specialisation and size class. We consider eight farm specialisations and two size classes as provided in Table 2, i.e. we have 16 ( $8 \times 2$ ) farm groups in total. Farm specialisation (principal type of farming) is defined in terms of the dominant farm activity, or that which has a share of standard output (SO) in total farm SO larger than a certain threshold defined by the [European Commission \(2010\)](#). We define two size classes: small farms with SO smaller than 250,000 Euros and large farms with SO greater than 250,000 Euros (see Table 2).

The methodology for constructing farm typologies in the FADN changed in 2009. The methodology switched from the old system based on the Standard Gross Margin (SGM) to the new system using SO. The SGM is the average value of output minus certain specific costs of each agricultural product in a given region calculated over the reference period of three successive years. SO is the average monetary value of the agricultural output valued at farm-gate price for each agricultural product in a given region calculated over a reference period of five successive years. The SGM (SO) of a farm is calculated as the sum of

the SGM (SO) of each agricultural product produced on the farm multiplied by the production level. Thus, the economic size of farms is calculated as the farm size expressed in Euros of SGM or SO, whereas the production specialisation is determined by applying thresholds for the dominant farm activities of farm groups based on share of SGM or SO.

Table 3 summarises the number of observations available for each farm type and size class by MS and aggregated at the EU-27 level for the period 1989–2013. The second column summarises the total number of observations by country; the remaining columns provide the available observations by farm specialisation (or type) (columns 3–10) and size class (columns 11 and 12). Countries with a larger number of NUTS 2 regions, such as France and Germany, have many observations (6,783 and 9,903, respectively) compared to countries with few NUTS 2 regions, such as Denmark (with only 336 observations).

Additionally, old Member States (EU-15) have more observations than new Member States (EU-12) because they have FADN data for a longer period. For example, EU-12 countries that joined the EU in 2004 or later<sup>6</sup> have at least six observations per farm specialisation, while EU-15 countries have at least 21 observations. Overall, at the EU-27 level, there are 49,630 observations in our dataset.

### 3.2. Variable choice and definition

The dependent variable – *farm group share*,  $s_{i,t}$  – used in estimating equation (4) is defined as the ratio of the number of farms in a given farm group to the total farm population calculated at the NUTS 2 level and annually for the period 1989–2013. Each farm in the FADN is assigned a weighting factor that measures the number of farms it represents in the total farm population. This weighting factor is used to calculate the dependent variable. The weighting factor in the FADN is derived from the number of farms in the population, available from the FSS, and the number of farms surveyed in the FADN. The FSS employs the same farm typology as the FADN. Hence, a farm group share is obtained as the sum of weighting factors across all farms in the FADN belonging to the farm group divided by the total number of weighting factors in the FADN.

The methodology change for the calculation of farm typologies in the FADN complicates the construction of farm groups, as no unique farm classification is available for the whole period 1989–2013. However, the FADN database offers classification from 2004 onwards for the SO approach and until 2009 for the SGM approach, resulting in five years of overlap. To extend the SO classification to years previous to 2004, one would need to re-classify the population and the FADN sample. This extension would require the availability of FADN and FSS data at the farm (micro) level, which is not possible due to the confidentiality issues. To overcome this problem, a

6 Bulgaria and Romania joined the EU in 2007.

**Table 3.** Number of observations by farm group used in the estimation: farm specialisation and economic size class

(1)	All (2)	Farm specialisations (type of farming)								Economic size class	
		Field crops (3)	Horticulture (4)	Permanent crops (5)	Grazing livestock (6)	Granivores (7)	Mixed cropping (8)	Mixed livestock (9)	Mixed both (10)	Small farms (11)	Large farms (12)
BL	3,339	441	399	378	462	420	357	441	441	1,701	1,638
DK	336	42	42	42	42	42	42	42	42	168	168
DE	9,903	1,345	1,135	927	1,366	1,345	1,074	1,345	1,366	5,174	4,729
EL	2,247	396	375	291	333	189	270	123	270	1,869	378
ES	4,675	585	626	563	710	605	542	521	523	2,588	2,087
FR	6,783	924	882	798	882	882	756	819	840	3,591	3,192
IR	357	84			84	21		84	84	189	168
IT	6,300	798	819	798	840	777	798	672	798	3,339	2,961
NL	3,780	483	504	441	504	462	462	441	483	1,848	1,932
AT	1,035	120	60	120	165	180	90	150	150	705	330
PT	1,638	231	252	168	231	252	231	105	168	1,071	567
SE	1,305	180	165		240	225	105	180	210	705	600
FI	750	105	120	45	120	120	75	75	90	465	285
UK	3,108	462	357	231	462	378	294	462	462	1,533	1,575
CZ	672	96	84	72	84	84	78	84	90	348	324
HU	660	84	78	84	84	84	84	78	84	336	324
PL	1,284	186	156	102	180	192	120	162	186	768	516
SI	90	12	12	6	12	12	12	12	12	48	42
SK	318	48	12	48	42	42	42	36	48	156	162
EE	84	12	12	6	12	12	6	12	12	48	36

LT	90	12	12	6	12	12	12	12	12	48	42
LV	84	12	12	6	12	12	6	12	12	48	36
CY	84	12	12	12	12	12	12	6	6	48	36
MT	72	6	12	6	12	12	6	12	6	48	24
BG	273	36	36	33	36	36	36	27	33	144	129
RO	363	48	48	45	45	48	42	39	48	192	171
EU27	49,630	6,760	6,222	5,228	6,984	6,456	5,552	5,952	6,476	27,178	22,452

Source: Authors' calculation based on FADN data. BL = Belgium and Luxembourg aggregated.

transition probability matrix is calculated based on the time span for which both classifications are available.<sup>7</sup> It provides the probability that a farm with a certain SGM class falls into a specific SO class. An example of the calculation is provided in Appendix A.2. With this transition probability matrix, all farms based on the SGM classification are reclassified into the SO classification. An example of the resulting time series of farm groups for the Netherlands (NL) is illustrated in Figure 1. The left-hand panel reports the total number of represented farms by farm groups, while the right-hand panel presents the farm group shares. The farm group shares are used as the dependent variable in the MCI model (inverse logarithm of the dependent variable of equation (5)).

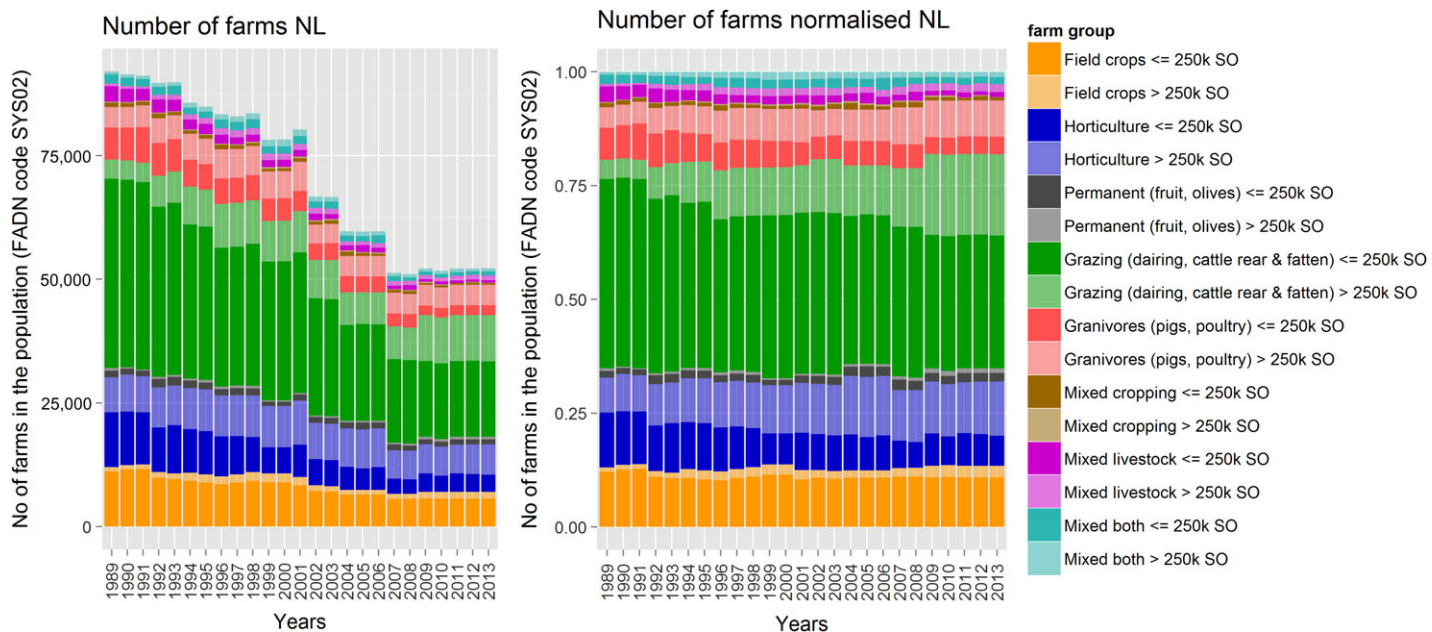
We use seven sets of explanatory variables,  $X_{k,i,t}$ , in our analysis: (i) input and output prices, (ii) population, (iii) subsidies, (iv) a dummy for decoupling, (v) income, (vi) macroeconomic variables and (vii) natural conditions. Tables 4 and 5 contain the descriptive statistics. The sources of the explanatory variables are the FADN, CRU TS 1.2 (Mitchell et al., 2003), EUROSTAT (EUROSTAT, 2012, 2013, 2014), World Bank (Worldbank, 2014), CAPRI, Corine land cover (EEA European Environment Agency, 2014) and EUGIS (EUGIS data base et al., 2008). Note that the data source also determines the regional resolution of the explanatory variables. FADN-based variables are farm group- and NUTS 2-specific. The highest resolution of other data sources is the NUTS 3 regional level. For example, EUROSTAT- and CAPRI-based variables are at the country level, while EUGIS variables are at the NUTS 3 level and FADN variables are at the farm level. The NUTS 3 and farm-level variables were aggregated to be farm group- and NUTS 2-specific, respectively.<sup>8</sup>

We consider input and output prices from CAPRI at the country level and FADN prices at the farm group level (Table 4). Alongside country-level prices, we also include farm group-specific output prices from the FADN, as they may capture the possible differences in price level across different farm groups induced by product quality differences and other factors (e.g. time of sale, marketing channel used). Prices probably differ in their impacts on farm group shares depending on the production specialisation. Farm group shares are expected to increase when prices of products in which the groups are specialised increase, while prices of substitutes are expected to decrease the shares. Input prices are expected to have a negative impact on farm group shares and this effect increases with the importance of a given input in the production process.

Managerial ability often determines the dynamics of structural processes because it is a key factor determining the allocation of farms' resources and the adoption of innovative technologies (Boehlje, 1992; Goddard et al., 1993). We include the variable *age of farm holder* to partially capture

7 We use 6-year averages of the yearly transition probabilities.

8 Only the country-level variables are equal for each NUTS 2 region and farm group, the remaining variables are entirely NUTS 2- and farm group-specific.



**Fig. 1.** Number of represented farms and shares by farm group in the Netherlands, 1989–2013.

*Note:* Farm group shares before 2004 are estimated using the transition matrix. Note that the farm group shares are calculated at the NUTS 2 level, while the shares presented in the figure are at the country level; they are weighted averages over NUTS 2 shares.

*Source:* Own calculation based on FADN data from the EU Commission-FADN Unit.

**Table 4.** Descriptive statistics for the economic explanatory variables used in the estimation for the EU-27

Variable category	Variable group and name	Mean	Standard deviation	Median	Unit	Regional resolution	Source
Macroeconomic variables	Interest rate (interest rate)	2.13	3.92	2.28	Per cent	Country level	EUROSTAT
	GDP growth rate (growth rate)	5.99	7.49	4.91			World Bank
	Unemployment rate (total)	8.78	10.55	7.95			EUROSTAT
	Unemployment rate (total, female)	9.63	11.75	8.46			
	Unemployment rate (total, male)	8.25	9.99	7.40			
	Unemployment rate (total, age >25)	7.36	8.93	6.42			
Population	Unemployment rate (total, age ≤25)	19.49	23.66	19.13		Farm group specific	
	Age of holder	48.8	23.2	48.3	Years		FADN
Input and output prices	Population density	275.3	57.2	135.0	Inh. p. km <sup>2</sup>	NUTS 3	EUROSTAT
	CAPRI Beef	2,998.4	4,626.7	2,983.9	€ per ton or index	Country level	CAPRI
	CAPRI Cereals	140.2	216.3	134.0			
	CAPRI Eggs	1,067.2	1,646.7	1,023.0			
	CAPRI Electricity	1,041.1	1,606.5	1,000.0			
	CAPRI Fruits	789.5	1,218.3	612.6			
	CAPRI Fuels	649.5	1,002.3	604.9			
	CAPRI Grass	15.0	23.1	13.1			
	CAPRI Heating gas and oil	481.8	743.4	455.5			
	CAPRI Maintenance buildings	991.2	1,529.5	1,000.0			
	CAPRI Maintenance materials	977.4	1,508.1	996.1			
	CAPRI Oil seeds	357.7	551.9	309.1			
	CAPRI Other animals output	1,000.8	1,544.2	991.9			
	CAPRI Other crops	998.3	1,540.3	999.6			
	CAPRI Other industrial crops	1,179.2	1,819.5	1,000.0			
	CAPRI Other inputs	1,027.0	1,584.7	1,000.0			
	CAPRI Pharmaceutical inputs	1,013.6	1,564.1	1,000.0			

CAPRI Plant protection	1,060.5	1,636.3	1,004.2
CAPRI Pork meat	1,457.2	2,248.4	1,437.0
CAPRI Potatoes	170.5	263.1	141.6
CAPRI Poultry meat	1,219.7	1,882.0	1,161.2
CAPRI Raw milk at dairy	332.8	513.5	316.8
CAPRI Renting of milk quota	817.7	1,261.7	810.0
CAPRI Seed	1,027.6	1,585.6	996.9
CAPRI Services input	966.6	1,491.5	987.8
CAPRI Sheep and goat meat	3,800.7	5,864.7	3,543.9
CAPRI Sugar beet	41.9	64.7	42.2
CAPRI Vegetables	491.5	758.4	417.7
PC of animal and crop input prices (INPO)	3,814.9	5,886.6	3,725.5
PC of animal and crop input prices (EGAS)	3,290.1	5,076.8	3,206.8
PC of animal input prices	-162.2	250.3	-34.7
PC of crop input prices	1,624.1	2,506.0	1,564.3
PC of other crop input prices (FRUI)	1,721.1	2,655.8	1,465.8
PC of other crop input prices (OCRO)	882.0	1,361.0	881.8
FADN Barley	146.6	70.8	141.6
FADN Cereals	160.2	75.6	149.8
FADN Dairy milk	321.5	154.7	312.2
FADN Eggs	1,276.7	701.3	1,013.7
FADN Oats	148.5	74.9	137.6
FADN Oil seeds	330.8	179	250.7
FADN Other animals	1950.3	1026.9	1002.1
FADN Other arable crops	430.4	202.8	202
FADN Potatoes	217.6	103.7	176
FADN Rape seed	270.3	157.1	235.5
FADN Rye and meslin	151.1	86.9	140.1
FADN Soft wheat	158	77.4	149.9

Farm group  
specific FADN

(continued)

**Table 4.** (continued)

Variable category	Variable group and name	Mean	Standard deviation	Median	Unit	Regional resolution	Source
Income and subsidies	Farm net value added per farm	49,887.2	23,323.5	35,529.6	€/Farm	Farm group specific	FADN
	Farm net value added per AWU	23,828.3	11,140.3	21,864.1	€/AWU		
	Farm net value added per UAA	1,298.1	606.9	821.3	€/ha		
	Total subsidies per farm	20,995	9,864.3	12,627.5	€/Farm		
	Total subsidies per AWU	9,634.3	4,526.6	7519.4	€/AWU		
	Total subsidies per UAA	335.4	157.6	270.2	€/ha		

*Note:* Mean and standard deviation of FADN price of other arable crops omitted due to several outliers. PC, principal component.

**Table 5.** Descriptive statistics for explanatory variables regarding natural conditions

Variable category	Variable group and name	Mean	Standard deviation	Median	Unit	Regional resolution
Corine land type characteristics <sup>a</sup>	Arable land	0.294	0.273	0.271	Share of total land	NUTS 3
	Artificial land	0.097	0.089	0.054		
	Forest and semi natural areas	0.347	0.320	0.330		
	Heterogeneous agricultural areas	0.117	0.108	0.096		
	Pastures	0.105	0.100	0.064		
	Permanent crops	0.035	0.040	0.009		
	Bodies of water	0.019	0.018	0.007		
	Wetlands	0.017	0.019	0.004		
	PC of Corine 2000 data (artificial)	−0.085	0.078	−0.115		
	PC of Corine 2000 data (forest)	0.030	0.028	0.026		
	PC of Corine 2000 data (pastures)	−0.103	0.095	−0.151		
	PC of Corine 2000 data (permanents)	−0.036	0.033	−0.061		
Topography and climate conditions <sup>b</sup>	PC of Corine 2000 data (water)	−0.042	0.039	−0.047	[0...1] Degree days (DD)  Days  Metre Per cent	NUTS 3
	Aridity index	0.739	0.682	0.767		
	AV grow. DD (10°C)(WGT10_mean)	1,050.4	968.6	880.6		
	SD grow. DD (10°C)(WGT10_sd)	2,159.1	1,991.0	1,810.0		
	AV grow. DD (5°C)(WGT5_mean)	2,155.7	1,987.9	1,913.4		
	SD grow. DD (5°C)(WGT5_sd)	4,431.1	4,086.1	3,932.9		
	AV veg. (10°C)(veg_period_10Celsius)	180.7	166.7	169.9		
	SD veg. (10°C)(_sd)	104.7	96.6	97.5		
	AV veg. (5°C)(veg_period_5Celsius)	259.5	239.3	250.1		
	SD veg. (5°C)(_sd)	153.0	141.1	144.4		
	Elevation 100 m raster	242.8	223.9	175.9		
	Slope 100 m raster	6.3	5.8	5.3		

Source: <sup>a</sup>Corine 2000 land use classification from [Corine 2000 database \(2005\)](#). <sup>b</sup>Data derived from EUGIS database and CRU TS 1.2; AV, arithmetic average of; SD = standard deviation of; PC, principal component with variable name of highest correlation with PC

managerial ability (Table 4). We obtain this variable from the FADN, calculated as the weighted average over all farm holders of a given farm group. The impact of farmers' age on structural change is probably ambiguous. Key and Roberts (2006) argue that older farmers possess more knowledge and experience and are better endowed financially (i.e. are less credit constrained), which is expected to lead to stronger performance of farm groups with older farm holders. On the other hand, farm holder age could have a negative impact on performance, as older farmers are often less likely to adopt new technologies or invest. Farmers' willingness to invest also depends on the availability of a successor. Unfortunately, this information is not available in the FADN.

We considered three variables related to *income*: farm net value added either per hectare, per total labour or per farm (Table 4). The aim of value added variables is to capture productivity, production intensity and financial performance of farms. Farm group shares are expected to be positively related to the farm group's value added.

Another set of explanatory variables includes *subsidies* granted under the CAP, a decoupling dummy and total subsidies measured either per hectare, per total labour or per farm. Total subsidies are calculated based on the FADN, and thus are farm group-specific. The decoupling dummy captures the effect of decoupling of direct payments introduced in 2005. Subsidies may affect farm structural change through negative and positive impacts on productivity, with the overall direction of these being open. The negative impact of subsidies on productivity may result from allocative and technical efficiency losses due to distortions in production structure and factor use (especially in the case of coupled subsidies), soft budget constraints, policy constraints (e.g. environmental requirements) and the shift of subsidies to less productive farms. The positive impact of subsidies may be due to investment-induced productivity gains caused by interactions of credit and risk attitudes with subsidies (subsidy-induced improved credit access, lower cost of borrowing, reduction in risk aversion) (Rizov, Pokrivcak and Ciaian, 2013). For example, Gocht *et al.* (2012) find a significant influence of agri-environmental payments and total subsidies on most of the farm groups analysed. Breustedt and Glauben (2007) and Goetz and Debertin (2001) argue that farm support increases farms' profitability and reduces farm exit. Ciaian, Kancs and Swinnen (2008) show that decoupled CAP payments may constrain farm structural change, as incumbent farms possessing rights to decoupled payments may have better access to land compared to new entrants. Rizov, Pokrivcak and Ciaian (2013) find CAP subsidies have a negative impact on farm productivity in the period before the decoupling, while after the decoupling the effect of subsidies on productivity appears to be positive.

*Macroeconomic and population density variables* aim to capture the impact of general economic conditions and competition for resources. We consider the unemployment rate, population density, interest rate and GDP growth rate (Table 5). The unemployment rate and population density capture

competition for labour with the non-agricultural sector in several dimensions. Off-farm employment opportunities may attract labour from agriculture and accelerate farm exit (Hallam, 1991; Harrington and Reinsel, 1995; Weiss, 1997; Hofer, 2002). On the other hand, off-farm income earned by family members may increase farmers' household income and, in particular, stabilise small farm businesses or part-time farmers in the short term (Goddard *et al.*, 1993; Harrington and Reinsel, 1995; Gebremedhin and Christy, 1996). We measure (lack of) off-farm employment opportunities by the unemployment rate and distinguish it by gender, since males, who are more likely to be heads of farm households, may respond differently to off-farm employment opportunities than females. Population density reflects another aspect of labour market competition: higher population density may imply a more industrialised region and thus stiffer competition for hired labour (e.g. seasonal workers) and may favour farm groups specialised in labour extensive products. Furthermore, a higher population density may increase urban demand for land, which, in turn, increases land rents (Binswanger, Deininger and Feder, 1993). An increased demand for land could favour farm groups that can afford to pay higher land rents. We expect the interest rate to negatively affect farm groups specialised in capital-intensive activities, such as granivore (poultry and pig fattening) production. GDP growth reflects the general dynamics of the macroeconomic environment, capturing general effects, such as demand for agricultural commodities, technical progress and competition for resources.

Important determinants of agricultural specialisation across regions are *natural conditions*. For instance, Fezzi and Bateman (2011) present some variables, such as growing degree days or altitude, in their analysis of land-use changes related to natural conditions. Uleberg *et al.* (2014) also discuss some climate variables affecting agriculture. Climate change recently became a focus of analysis of the determinants of structural changes. Mandryk, Reidsma and van Itersum (2012) provide a short overview of literature investigating climate change as a cause of structural changes. Climate change refers to changes in climatic conditions or climate variability that affect crop productivity, farmer income and land use (Olesen and Bindi, 2002; Bradshaw, Dolan and Smit, 2004; Berry *et al.*, 2006; Reidsma *et al.*, 2009; Bindi and Olesen, 2011). We consider variables indicating land types as well as those measuring topography and climate conditions (Table 4). All variables describing natural conditions are time-invariant, as they usually change minimally within the medium-term time horizon considered in this paper.

The Corine land use variables (Corine 2000, 2005) provide the percentage shares of the different land categories (e.g. arable land, pasture land) in a given region. These variables are locational factors and are expected to have diverse impacts on farm group shares. For instance, in regions endowed with arable land, we expect a greater share of the farm groups specialised in arable cropping.

The topography and climate variables are derived from the EUGIS database and include aridity, vegetation period, growing degree days, slope and

elevation. The climate-related variable aridity is calculated as an average annual precipitation (in millimetres) divided by five times the average annual temperature, truncated from above at 1 and from below at 0.<sup>9</sup> The higher the value, the less arid the region. Slope and elevation variables derive from a 100 m raster, and we expect them to have a positive impact on farm groups specialised in dairy production and suckler cows and a negative impact on cereal farms. The variables related to growing degree days (WGT) and the length of the vegetation period (veg\_period) are calculated for each region for the thresholds of 5 and 10°C as the mean and standard deviation across observed years. The variable WGT is a measure of heat accumulation and is calculated as the sum of the days in which monthly average temperatures are above the threshold of 5 and 10°C, multiplied by 30. The variable veg\_period measures the number of days with average temperatures above the threshold, thus capturing differences in duration and, by considering two thresholds, also the ‘quality’ of growing conditions between regions. The mean and the standard deviation values of WGT or veg\_period are expected to have a different impact on farm groups. For instance, if the vegetation period is long (i.e. high mean value), dairy farms are likely positively affected because the grazing period increases. However, a high standard deviation of vegetation period increases the risk of growing crops that require a longer vegetation period, and hence, those farm groups specialised in these crops are expected to be negatively affected because a higher risk level may reduce their investments, leading to a decrease in their share relative to other farm groups.

#### 4. Empirical model specification

We adjust the  $X_{k,i,t}$  in equation (4) to include not only the contemporary version of the variables introduced in the last section, but also the lagged values of independent and dependent variables to account for dynamic adjustments in farm structures over time. The adjustment of farm structures to changes in market and policy conditions is not instantaneous, and it typically takes time for full response to be realised. The delayed adjustment of farm structures may occur due to factors such as asset specificity, sunk costs, changing opportunity costs for labour, adjustment costs and the capital-intensive nature of agricultural production, which prevents farmers from switching costlessly and instantaneously between different production types (Zimmermann and Heckelei, 2012). We consider up to four lags for all variables except prices and natural conditions. Prices are lagged for only 1 year. Variables describing natural conditions are time-invariant and are primarily used to control for the regional heterogeneity of growing conditions and suitability of agricultural production across various farm groups.

Based on equation (4), the resulting model specification used in estimation is as follows:

9 The calculation of the aridity index is inspired by the Walter and Lieth climate diagrams (Walter and Lieth, 1967).

$$\log(s_{i,t}) = \alpha_1 + \sum_{j=2}^M \alpha'_j d_j + \sum_{k=1}^K \sum_{j=1}^M \sum_{r=0}^R \beta_{k,i,r} d_j \log(X_{k,i,t-r}) + \varepsilon_{i,t}, \quad s_{k,i,t-r} \in X_{k,i,t-r} \quad (6)$$

Equation (6) implies a total of  $K \times m \times R + m$  parameters to be estimated, where  $r$  is the lag index and  $R$  is the total number of lags considered in the model.<sup>10</sup> Note that, for MS, which joined the EU later, the time series used are shorter (e.g. 2004–2013 for countries that joined the EU in 2004). To reduce the dimension of the estimated models (in total, we consider  $119 + 4 = 123$  variables),<sup>11</sup> we apply a forward selection algorithm for statistically significant variables. If we were to specify equation (6) with the same explanatory variables for all farm groups, it is very likely that most variables would be statistically insignificant for all farm groups. Therefore, we opt to estimate 16 (farm group) models per country, with one model for each combination of farm specialisation (or type) and size class. Hence, starting with the same overall set of variables, the forward selection is applied separately for each estimated model (farm group) and consequently may imply that the final set of explanatory variables with statistically significant coefficients will ultimately differ between farm group models. The resulting model specification for each farm group  $i$  separately is as follows:

$$\log(s_{i,t}) = \alpha_i + \sum_{k=1}^K \sum_{r=0}^R \beta_{k,i,r} \log(X_{k,i,t-r}) + \varepsilon_{i,t}, \quad s_{k,i,t-r} \in X_{k,i,t-r} \quad \text{and} \quad i = 1, 2, \dots, M \quad (7)$$

We estimate equation (7) with the OLS estimator for each farm group  $i$  and country using yearly observations across NUTS 2 regions. The forward selection begins with only an intercept and one of the available variables at a time and adds the variable, which increases the most the Bayesian information criterion (BIC) of the model. This process is repeated with the remaining variables until the resulting model can no longer be improved.<sup>12</sup> The estimated dependent variable of this resulting model is then transformed and normalised (equation (5)) to obtain the estimated farm group shares across NUTS 2 regions.

To measure the goodness of fit of the estimated farm group shares compared with the observed shares, we calculate the following coefficient of determination, which is farm group-specific:

10 Except for variables regarding prices and natural conditions.

11 For all variables in Tables 4 and 5 and their respective lags (119) and the four lagged farm group shares for each model.

12 Note that due to the path dependency problem in the forward selection algorithm, the model with the highest predictive power may not be necessarily selected. To avoid this, we would have to estimate all models with all possible combinations of explanatory variables, which is not possible computationally.

$$R_i^2 = 1 - \frac{\sum_{t=5}^T (s_{i,t} - \hat{s}_{i,t})^2}{\sum_{t=5}^T (s_{i,t} - \bar{s}_{i,t})^2} \quad (8)$$

where  $\bar{s}_{i,t}$  is the average farm group share belonging to group  $i$  at time  $t$ , and  $T$  is the total number of available years.<sup>13</sup>

## 5. Results and discussion

### 5.1. Summary results of the farm group models

As mentioned above, we estimate up to 16 models for each farm group and country. We refrain from presenting all the estimated coefficients and instead report some statistics of fit of the estimated regressions and the summary of the decomposition results of the drivers of farm structural change. We also present the elasticities of farm structural change with respect to the variable sets considered in the estimations.

Table 6 reports the mean, median, minimum and maximum value for the coefficients of determination over the 16 farm groups for 16 countries.<sup>14</sup> The coefficient of determination ( $R^2$ , see equation (8)) is on average relatively high, ranging between 80 per cent in Spain and 96 per cent in France.<sup>15</sup> For countries with a coefficient of determination of almost 100 per cent (see footnote 14), the number of observations is very low, hence resulting in a nearly perfect fit due to the forward selection. Most of these countries have only one NUTS 2 region. Nevertheless, most of the remaining countries show relatively high coefficients of determination, indicating a very good representation of farm structural development across countries, although a small number of farm groups, such as some in the Czech Republic (34 per cent) or Hungary (47 per cent) (see the minimum values in Table 6), are not so well explained through our estimated models.

### 5.2. Comparison of estimated and observed farm group shares

Next, we compare the estimated (*predicted*) and observed farm group shares for selected countries over the considered period. Note that the reported period may differ by country depending on its date of EU accession as well as

13 In equation (5), the starting value of time index  $t$  is set equal to five, because the estimated models include up to four lags and therefore the fifth observation in time is the earliest possible point at which to compare the observed and the predicted shares.

14 The remaining countries (Denmark, Slovenia, Slovakia, Estonia, Latvia, Lithuania, Cyprus, Malta, Bulgaria and Romania) are not reported because they have a median of one or almost unity and show only little variation between farm groups, as they have shorter time series or fewer NUTS 2 regions.

15 For Germany, we tested for heteroskedasticity with the Breusch–Pagan test and detected heteroskedasticity for some farm groups. As most of the estimates were significant at a 5 per cent significance level (using heteroskedasticity corrected standard errors), we refrained from any correction procedure to achieve higher estimator efficiency. As the variable selection process is based on the BIC rather than on the  $p$ -value for each estimate, the heteroskedasticity issue is not relevant in this context.

**Table 6.** Summary results of the farm group-specific coefficient of determination by country

Country	Mean	Median	Min	Max	Country	Mean	Median	Min	Max
BL	0.919	0.926	0.791	0.988	AT	0.926	0.967	0.703	0.998
DE	0.932	0.94	0.862	0.966	PT	0.898	0.913	0.696	0.999
EL	0.917	0.939	0.778	0.999	SE	0.851	0.894	0.559	0.998
ES	0.798	0.794	0.584	0.988	FI	0.914	0.939	0.799	0.999
FR	0.958	0.976	0.809	0.996	UK	0.81	0.86	0.517	0.986
IR	0.909	0.976	0.673	1	CZ	0.852	0.915	0.342	0.974
IT	0.863	0.894	0.698	0.98	HU	0.868	0.931	0.467	0.996
NL	0.874	0.888	0.679	0.978	PL	0.902	0.929	0.768	0.991

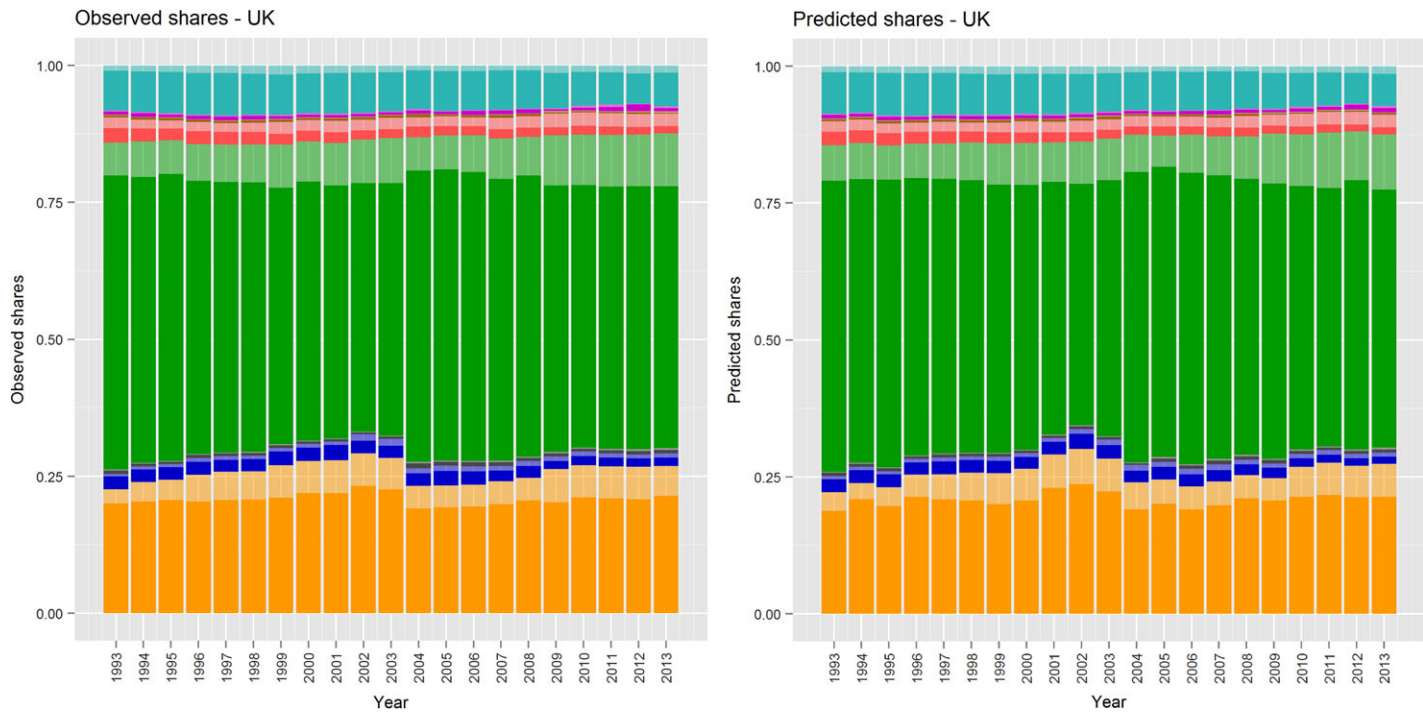
*Source:* Authors' calculation based on FADN data from the EU Commission-FADN Unit.

the lags considered for the dependent variable. Due to the large amount of data, we focus only on selected countries: the UK and the Netherlands. The results are reported in Figures 2 and 3. For each selected country, we present the observed and estimated farm group shares (maximum 16 classes) at the country level (weighted average over NUTS 2 regions) (upper panel of each figure) and NUTS 2 level (middle panel), as well as the percentage point difference between the observed and estimated share at the NUTS 2 level (bottom panel). Visual inspection of the figures shows that there is a large heterogeneity in farm structure, both across countries and between NUTS 2 regions within a given country. The results indicate that the observed farm group shares are relatively well recovered with the estimated models. Although the deviations between predicted and observed shares at the aggregated country level appear to be small, at NUTS 2, they are larger. For example, in the case of the UK, the largest deviation between observed and estimated shares is visible for some farm groups in UKC, UKE and UKF NUTS 2 regions (e.g. field crops and grazing livestock) where the difference is slightly above 5 per cent in some years (e.g. in 2005 and 2010–2012). For the rest of the farm groups and regions, the difference is almost always within the  $\pm 5$  per cent interval (Figure 2, bottom panel). Regions with a fewer number of farm groups (UKN and UKL) clearly show a smaller deviation than other regions. For the Netherlands, the deviation between observed and estimated shares across farm groups and NUTS 2 regions remains within the  $\pm 10$  per cent interval or less (Figure 3, bottom panel).

In general, the estimations capture the trends regarding farm structure development observed in the actual data relatively well. For example, at the country level in the Netherlands and UK, we observe an increase in the farm group grazing livestock of large size ( $SO > 250k$ ) largely at the expense of small-sized ( $SO \leq 250k$ ) grazing livestock in both the observed and estimated data. We also observe that, for most of the farm groups, both size classes (small and large) are present in these two countries (Figures 2 and 3). In the Netherlands, we observe a very heterogeneous farm structure across NUTS 2 regions. There are regions that are dominated by horticulture (NL33), grassland production (NL12, NL21, NL22, NL31) and field cropping (NL23) farms in the Netherlands. The estimation recovers this regional heterogeneity of farm groups relatively well (Figure 3).

### 5.3. Decomposition of the estimated effects

To better identify the importance of various drivers of farm structural change, we decompose the variance of the dependent variable – farm group shares – into the relative contributions of each explanatory variable for all country models using the approach first proposed by Fabbri (1980). According to Grömping (2015), this measure is the metric of choice when the estimated effects are to be decomposed, as it meets almost all of the key requirements for describing relative importance of explanatory variables and is less



**Fig. 2.** Observed and predicted farm group shares at country and NUTS 2 levels and absolute difference at NUTS 2 level in the UK.  
*Source:* Authors' own compilation.

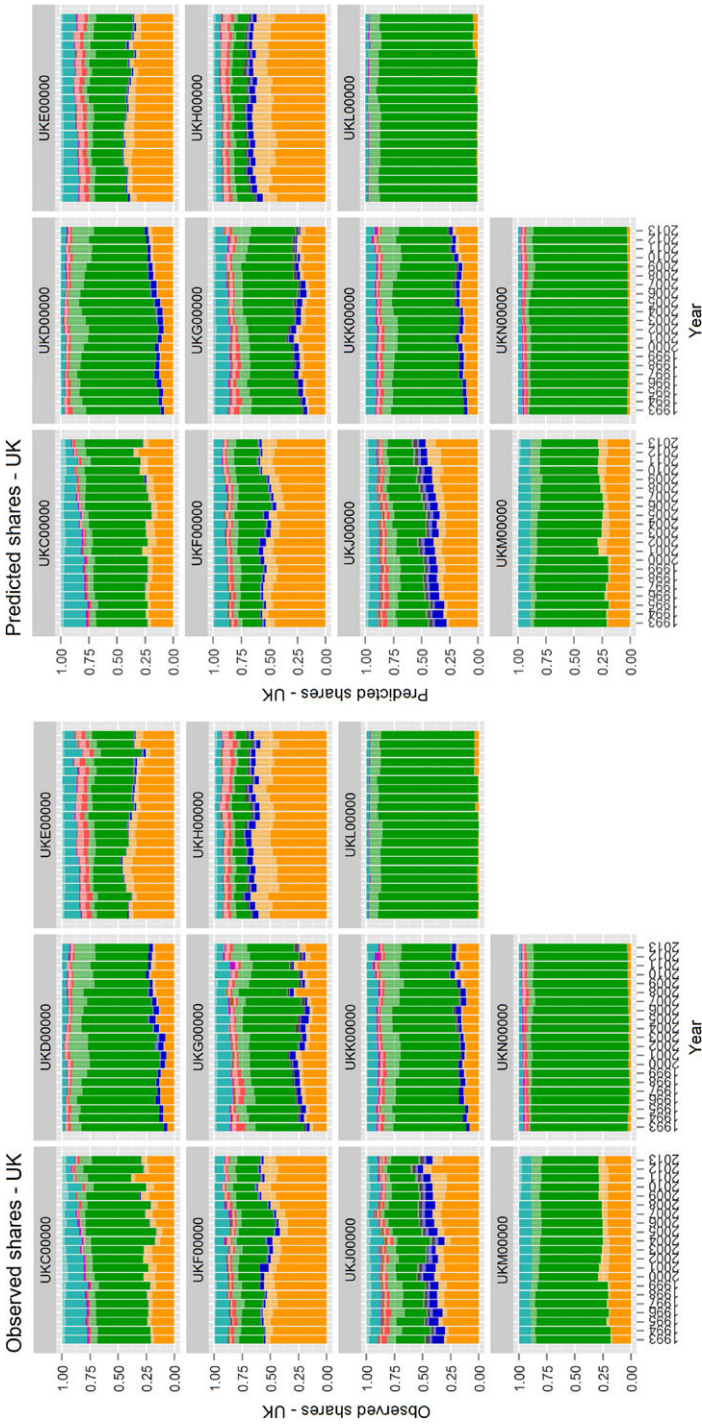


Fig. 2. Continued

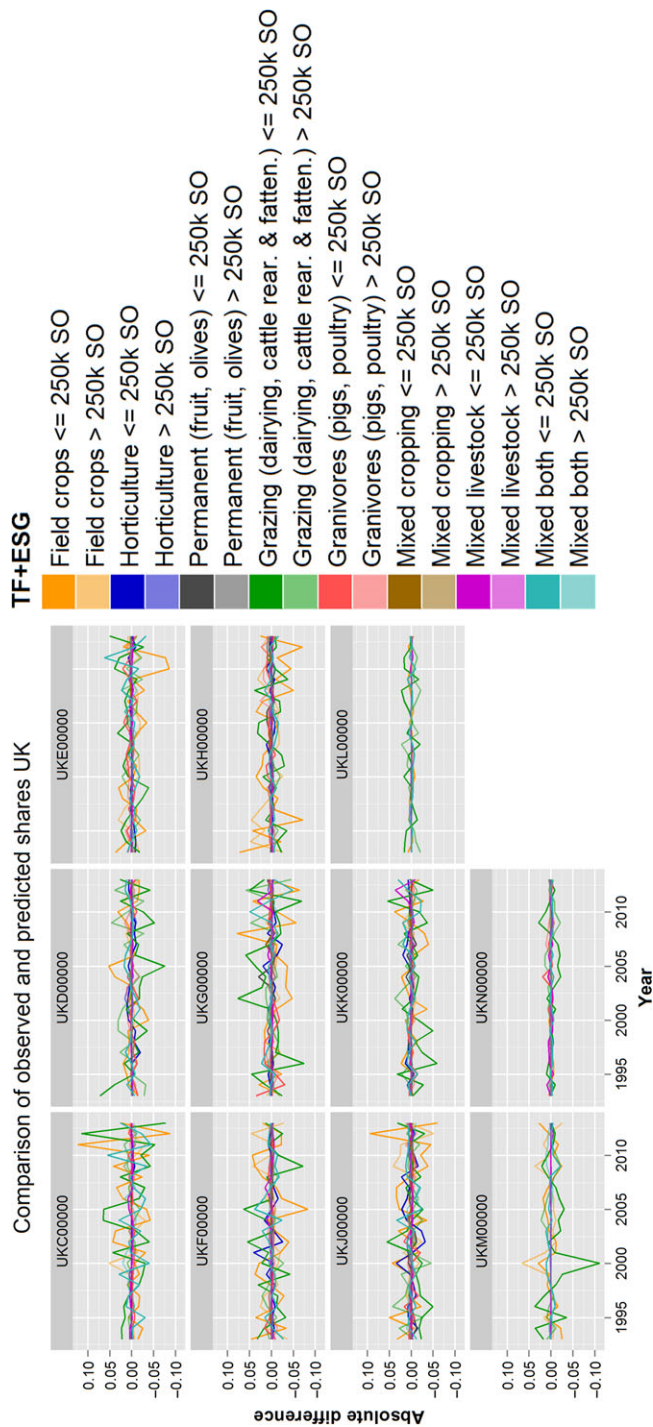
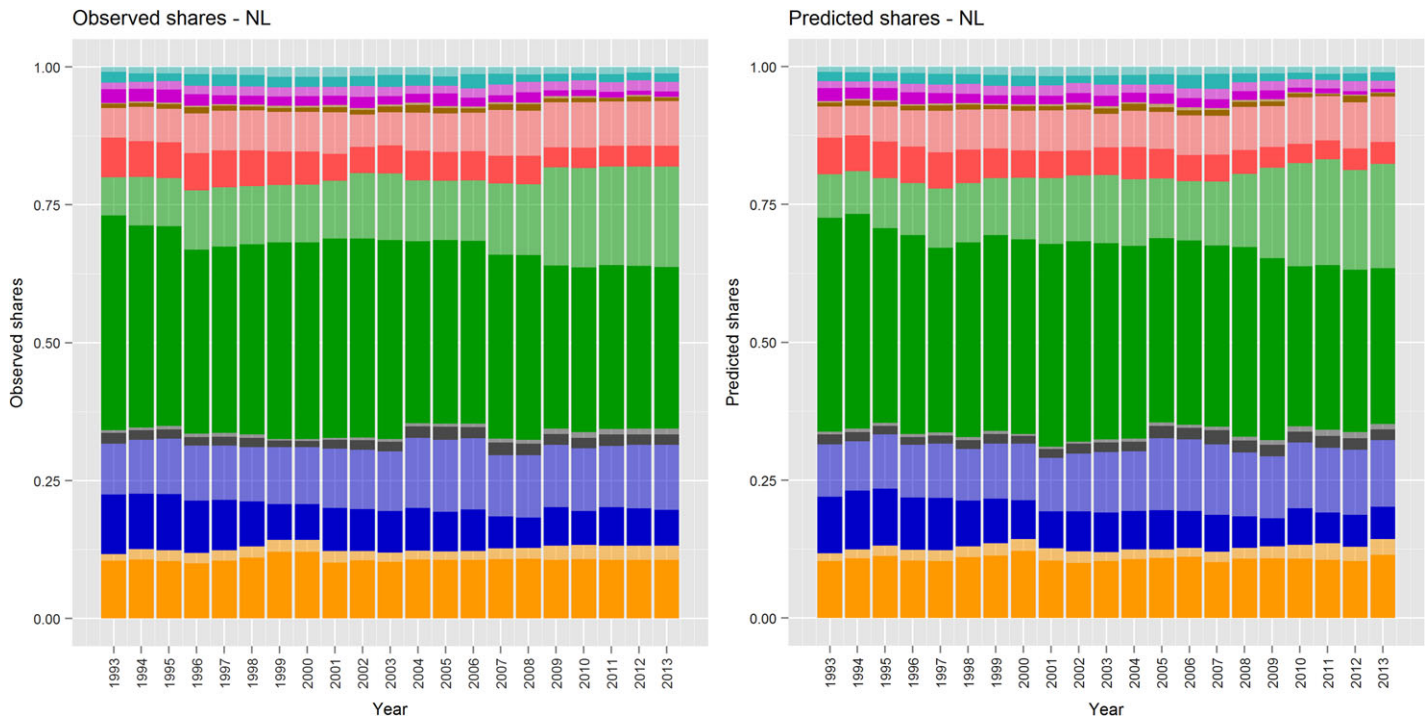


Fig. 2. Continued



**Fig. 3.** Observed and predicted farm group shares at country and NUTS 2 levels and absolute difference at NUTS 2 level in the Netherlands.  
*Source:* Own compilation.

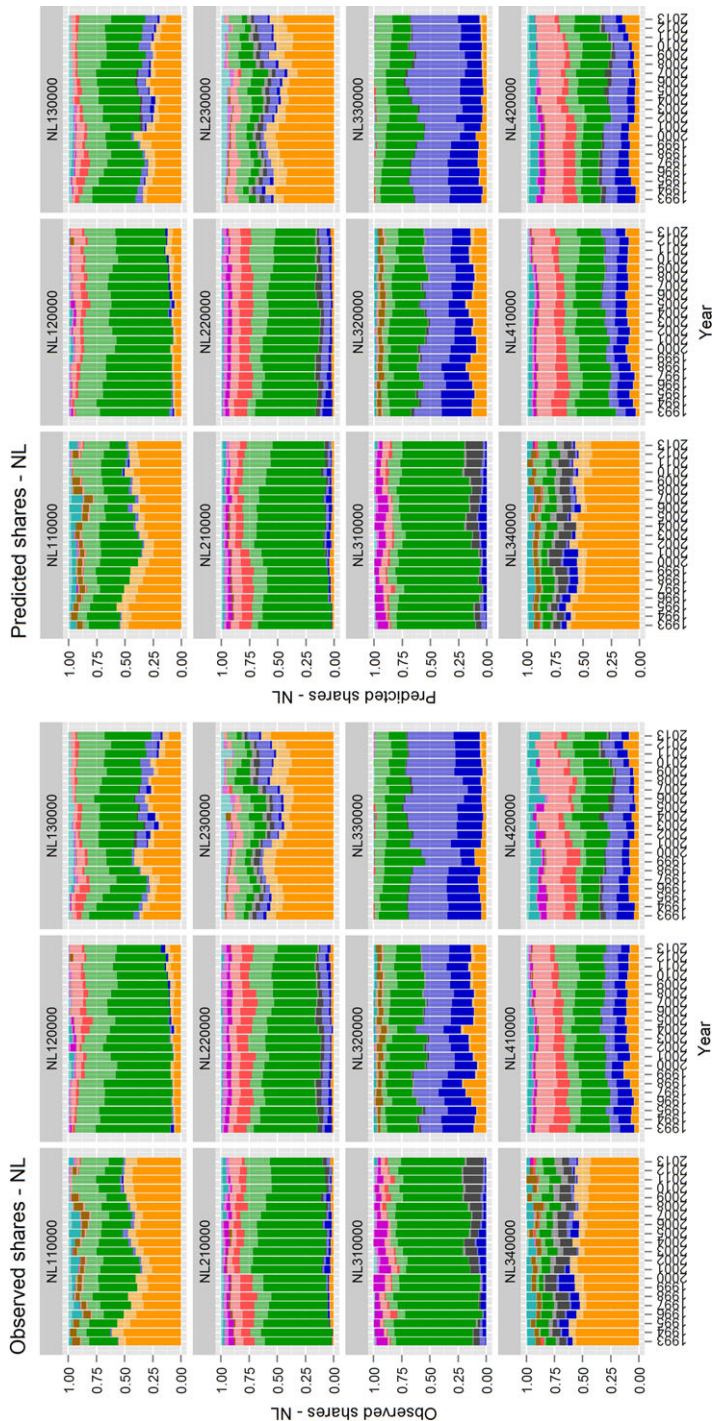


Fig. 3. Continued

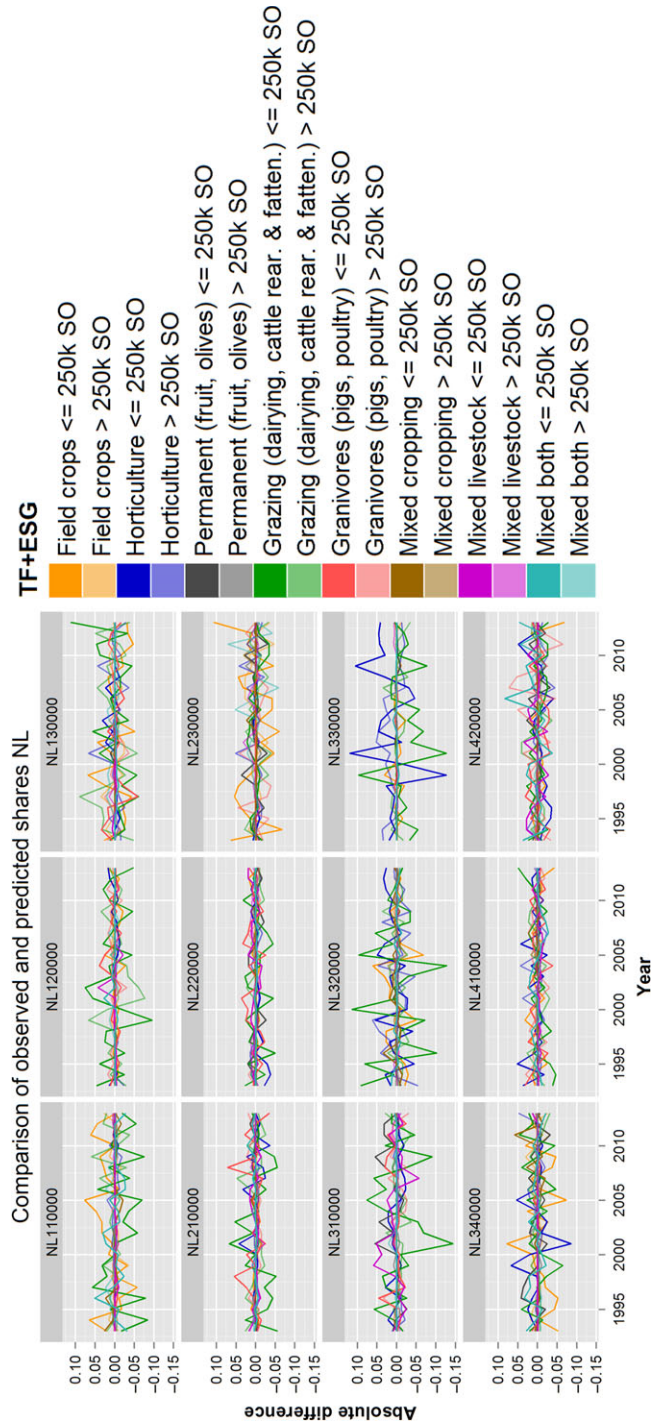
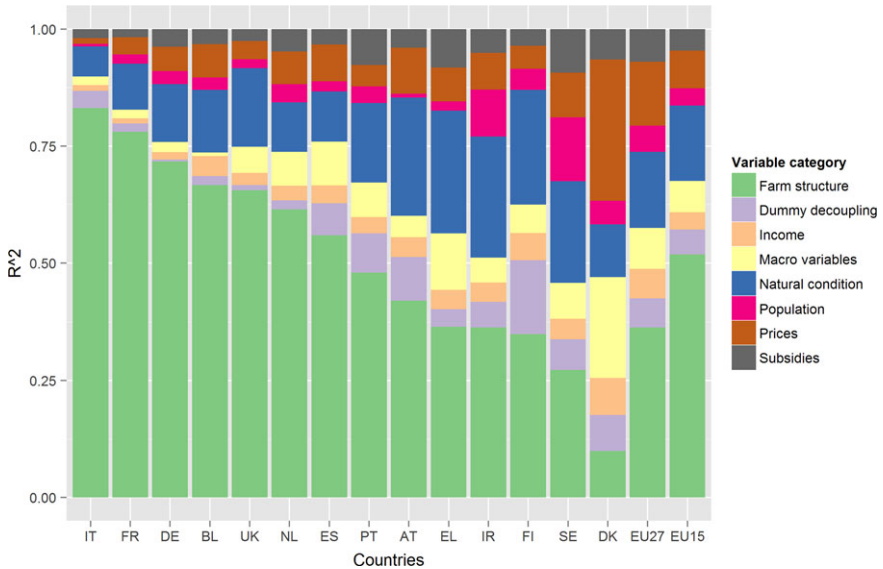


Fig. 3. Continued



**Fig. 4.** Variance decomposition by country in the EU-15.

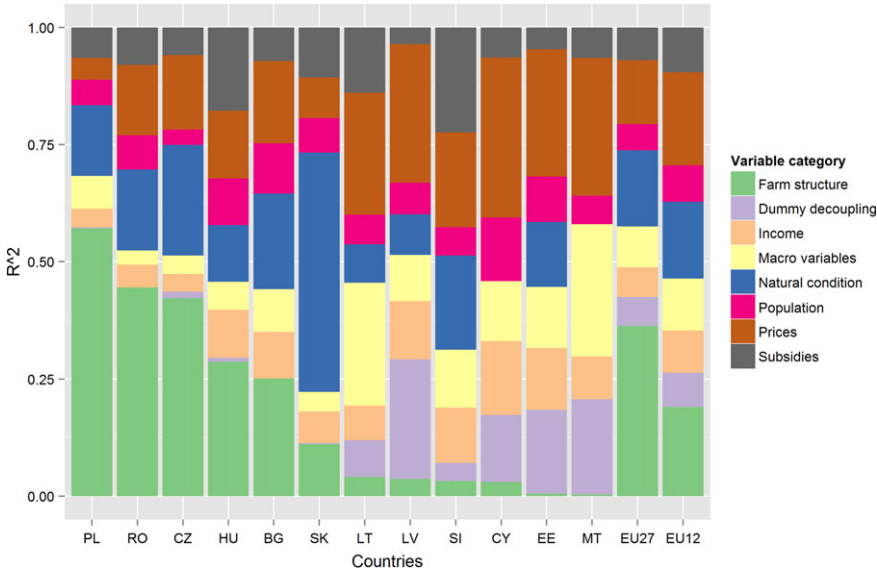
*Notes:* Belgium and Luxemburg are treated as one MS.

*Source:* Authors' own compilation.

computationally demanding than alternative approaches. We report the results by MS and aggregate them at the EU-12, EU-15 and EU-27 levels for the following variable sets: prices, population (population density and age of holder), macro variables, decoupling dummy, subsidies, income (added value), natural conditions and farm structure (lags of dependent variables).

Figure 4 shows that the past farm structure (i.e. the lagged farm group shares) is the main determinant of the farm structure in the EU-27. The past farm structure explains approximately 36 per cent of the variance of the farm group shares. Past farm group shares strongly influence current ones, indicating that adjustment processes carry on over several years. Natural conditions are also important drivers of farm structure, explaining approximately 16 per cent of the variance of farm group shares. The remaining variables explain 48 per cent of the total variance in the EU-27, with prices explaining 14 per cent, macro variables 9 per cent, subsidies 7 per cent, population 6 per cent, income 6 per cent and dummy decoupling 6 per cent.

Figures 4 and 5 reveal a striking difference between the EU-15 and EU-12 in the contribution of various drivers to farm structural change. The main difference between the EU-15 and EU-12 is the importance of lagged farm group shares in explaining the regional difference and evolution of farm groups. The past farm structure explains almost 52 per cent of the variance of farm group shares in the EU-15, while its contribution is much smaller in the EU-12, at approximately 19 per cent. In other words, these results imply a more rigid farm structure in the EU-15 than in the EU-12. This difference



**Fig. 5.** Variance decomposition by country in the EU-12.

*Source:* Authors' own compilation.

could be attributed to stronger structural changes taking place in the EU-12 due to their recent EU accession and the ongoing transition process. The countries with the largest impact of past farm structure (more than 70 per cent) are France, Italy and Germany, where farm structure is highly rigid and relatively inert to external drivers. In the EU-12, only Poland has a rigid farm structure comparable to the EU-15 average. The most dynamic farm structure tends to be observed in Malta, Lithuania, Latvia, Slovenia, Denmark and Estonia.

Natural conditions (land type and topography and climate) appear to be equally important in explaining farm structures across regions and structural change in both the EU-12 and EU-15, although with some variation across individual countries. They explain approximately 16 per cent of the variance of farm group shares in the EU-15 and EU-12, which is in line with our expectation that factors such as climate, slope and vegetation period reflect the diversity of growing potential across regions in the EU and thus determine the comparative advantage of various farm specialisations.

Subsidies and income have a stronger impact on farm structural change in the EU-12 than in the EU-15. Subsidies, the decoupling dummy and income contribute 5 per cent, 5 per cent and 4 per cent in the EU-15 and 10 per cent, 7 per cent and 9 per cent in the EU-12, respectively. The combined contribution of subsidy and the decoupling dummy variables is 10 per cent in the EU-15 and 17 per cent in the EU-12, which appears to suggest that future CAP reforms may exercise a significant influence on the development of farm structure, particularly in new Member States.

Macroeconomic variables (e.g. unemployment indicators, GDP growth rate, interest rate) and population variables (population density and farmers' age) account for 7 per cent and 4 per cent of the variation in farm group shares in the EU-15 and 11 per cent and 8 per cent of the variation in farm group shares in the EU-12, respectively. Macro variables are particularly important drivers in Malta, Latvia, Slovenia, Denmark and Greece. Population density and age explain a larger portion of structural change in countries such as Cyprus, Estonia, Ireland, Hungary, Bulgaria and Sweden.

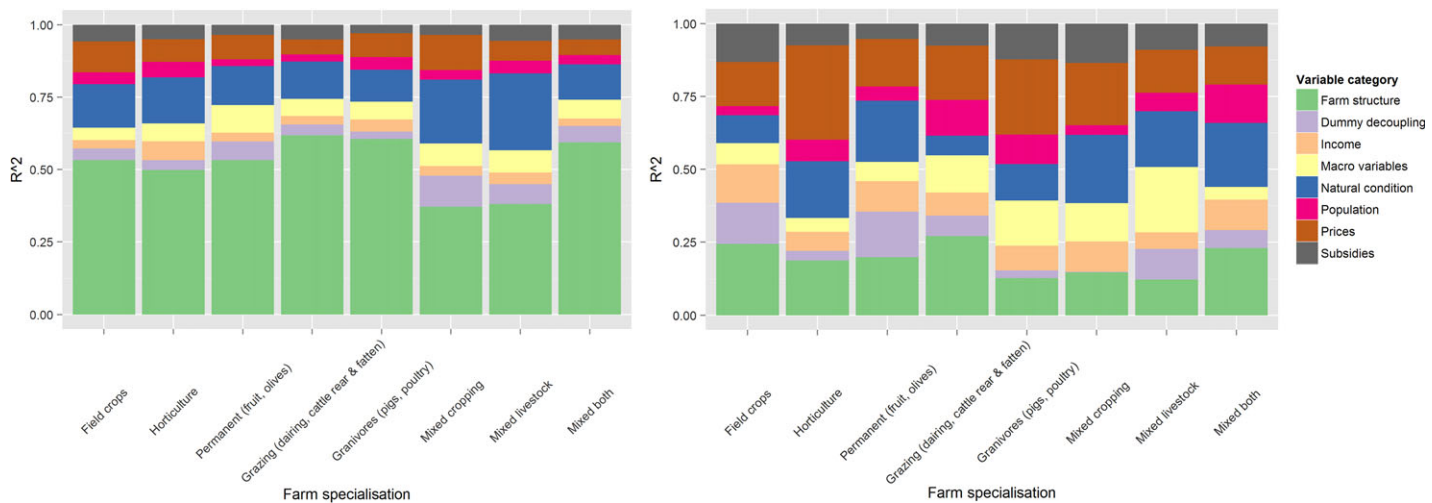
Finally, input and output prices explain structural change by 8 per cent in the EU-15 and 20 per cent in the EU-12. Compared to other variables, we would expect prices to have greater importance in driving farm structures. However, income variables may explain part of the price effects.

Figure 6 shows the variance decomposition by farm specialisation. The left-hand panel presents the results for the EU-15 and the right-hand panel for the EU-12. In general, there are no significantly different patterns observed between the farm specialisations, only that lagged farm group shares tend to contribute less to driving farm structure in mixed cropping and mixed livestock farms compared to other farm specialisations, particularly in the EU-15. Consistent with the results shown in Figure 4, past farm structure has a considerably stronger impact on different farm specialisations in the EU-15 than in the EU-12.

#### 5.4. Long-run elasticities of farm structural change

The impact of individual exogenous variables on farm structure as measured through their contribution to prediction may be misleading when analysing structural change, as it includes variation across regions in a country and does not show the full dynamic adjustments implicit in the estimated models. The estimated models are dynamic because they include lagged variables for both exogenous and dependent variables. To better account for dynamic adjustments in farm structure, we introduce shocks to selected exogenous variables in the estimated models and predict the future response of farm group shares until the year in which the annual change in a farm group share aggregated at the country level is below 0.5 percentage points. We use the predicted results to calculate elasticities that measure the response of farm group shares to different exogenous variables. Note that we do not perform predictions (and hence also elasticities) for natural conditions, as these variables are time-invariant in our model. Additionally, we only take into account those variables that have a statistically significant impact in our regressions.

To calculate elasticities, we run two scenarios: baseline (no shock) scenarios and scenarios with shocks. We define an autoregressive development as baseline, for which we predict the future development of farm group shares using the estimated models by assuming that no shock is applied to any explanatory variable. Note that even without introducing a shock to the exogenous variables, the farm group shares will change over time due to the



**Fig. 6.** Variance decomposition by farm specialisation in the EU-15 (left panel) and EU-12 (right panel).

*Source:* Authors' own compilation.

autoregressive process considered in the estimated models. In scenarios with shocks, we introduce a shock separately for each statistically significant explanatory variable, keeping other variables unchanged, and then use the estimated models to generate predictions for farm group shares. The shock for each explanatory variable is introduced over the whole simulated period, i.e. until convergence is reached. The variables are shocked in the year 2013, and this shock is permanently maintained for this variable over the whole simulation period. The shock impacts each farm group in 2014 at the earliest if the variable is lagged 1 year and in 2017 at the latest if the variable is lagged 4 years. Therefore, the simulation must run for at least 4 years to ensure that the impact of each variable is taken into account in the predicted values.

Elasticities are calculated as the ratio between the net percentage change in predicted farm group shares after convergence and the permanent percentage change in the shocked explanatory variable. The net percentage change is the difference between the relative change in predicted farm group shares after convergence in the shock scenario ( $\% \Delta \hat{s}_{i,k}$ ), minus the relative change in predicted farm group shares in the (autoregressive) baseline,  $\% \Delta \hat{s}_i$ . Consequently, we obtain

$$E_{i,k} = \left( \frac{\% \Delta \hat{s}_{i,k} - \% \Delta \hat{s}_i}{\% \Delta X_k} \right) = \left( \frac{\% \Delta \hat{s}_{i,diff}}{\% \Delta X_k} \right) \quad (9)$$

where  $E_{i,k}$  is the elasticity for farm group  $i$  with respect to explanatory variable  $k$  and  $\% \Delta X_k$  is the relative change in the exogenous variable over the simulation period.

Table 7 presents the elasticities calculated using equation (9) and aggregated at the EU-15 and EU-12 levels. We calculate the average of the absolute values of elasticities.<sup>16</sup> This indicates how much a specific category of explanatory variables influences farm group shares across all estimated models without taking into account the sign of the effects. The displayed values indicate that, on average, the farm group shares change in the range of between 29 and 117 per cent in response to a 100 per cent permanent change in a given explanatory variable. Income has the greatest impact on farm group shares in the EU-15, followed by macro variables (between 0.62 and 0.75). Subsidies and price variables have the smallest impact. In the EU-12, income has the greatest impact, followed by macro variables (between 0.51 and 1.17), whereas prices, subsidies and population variables have the smallest impact.

16 Elasticities for farm group shares smaller than 2.5 per cent (the average for the last four observed years, 2010–2013) are excluded from calculations reported in Table 7. This means that only more dominant farm groups are considered. As a result of this consideration, elasticities for mixed livestock farms in the EU-15 are excluded. After this adjustment, still some elasticities might be very high because of the high relative changes obtained for some small farm groups. To avoid distortion in the elasticities, these farm groups are also not considered in the calculations reported in Table 7.

**Table 7.** Summary of elasticities of farm structural change in the EU-15 and EU-12

EU aggregate	Category	Absolute mean value of elasticities
EU-15	Macro variables	0.62
	Population	0.35
	Prices	0.30
	Subsidies	0.29
	Income	0.75
EU-12	Macro variables	0.51
	Population	0.44
	Prices	0.29
	Subsidies	0.34
	Income	1.17

Source: Authors' own calculation based on FADN data from the EU Commission-FADN Unit.

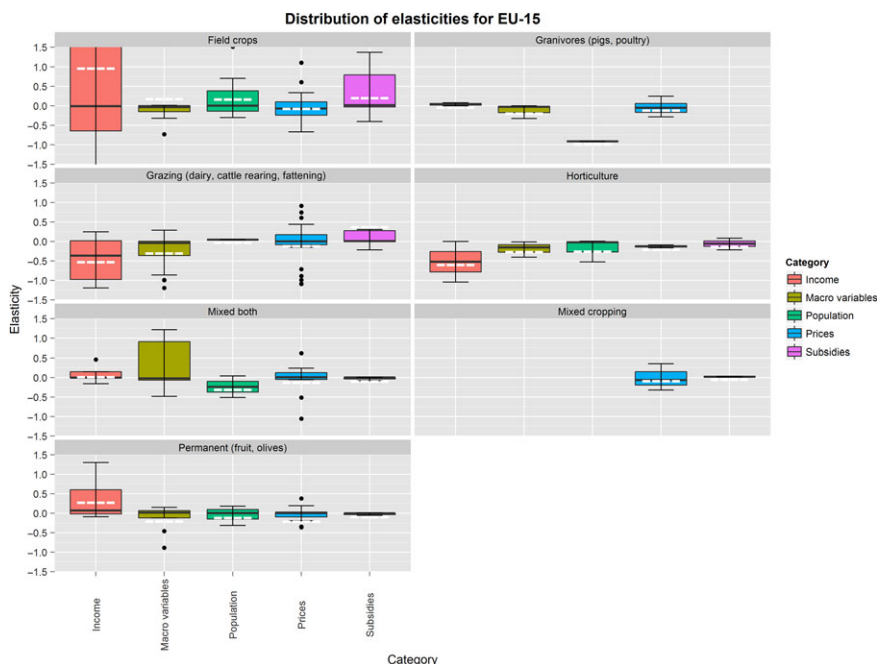
Figures 7 and 8 present the distribution of elasticities across NUTS 2 regions by farm specialisation for the five categories of explanatory variables (income, macro variables, population, prices and subsidies) in the EU-15 and EU-12.<sup>17</sup> In the EU-15, the elasticities with respect to income variables appear to have the largest magnitudes, followed by macro variables. In the EU-12, elasticities with respect to income and population variables have the largest magnitudes. In the EU-15, half of the elasticities are negative for almost all variable categories, while the other half are positive.<sup>18</sup> On the other hand, in the EU-12, some shocked variable categories, such as income, show for some farm groups that the majority of elasticities are greater than zero.

Note that income variables are calculated as the net value added per farm, per hectare and per total labour (annual working unit: AWU), and they are region- and farm group-specific. Contrary to expectations, these income variables tend to have negative impacts on the farm group shares at the median. The mean value for the EU-15 and for EU-12 is positive, while the median is almost zero for the former and negative for the latter. These counterintuitive results could be explained by the following: first, higher income levels may encourage production diversification even in the absence of overall farm expansion (e.g. when renting or buying additional utilised agricultural area (UAA) is expensive), causing a contraction in some production specialisations and an increase in others. Second, it is possible that the net value added per hectare alone may decrease, while the total agricultural area of certain farm groups expands (e.g. due to decreasing returns to scale).

The interpretation of the estimated coefficients for variables is not straightforward, particularly with respect to the direction of the effect. This is

17 The boxplots are restricted to lie within  $-1.5$  and  $1.5$ . Additionally, the mean is inserted with a white dashed line. The y-axis is limited for presentation reasons. For some boxplots, the mean or some whiskers are not displayed because of large outliers.

18 The median of the elasticities is indicated by the thick black line.



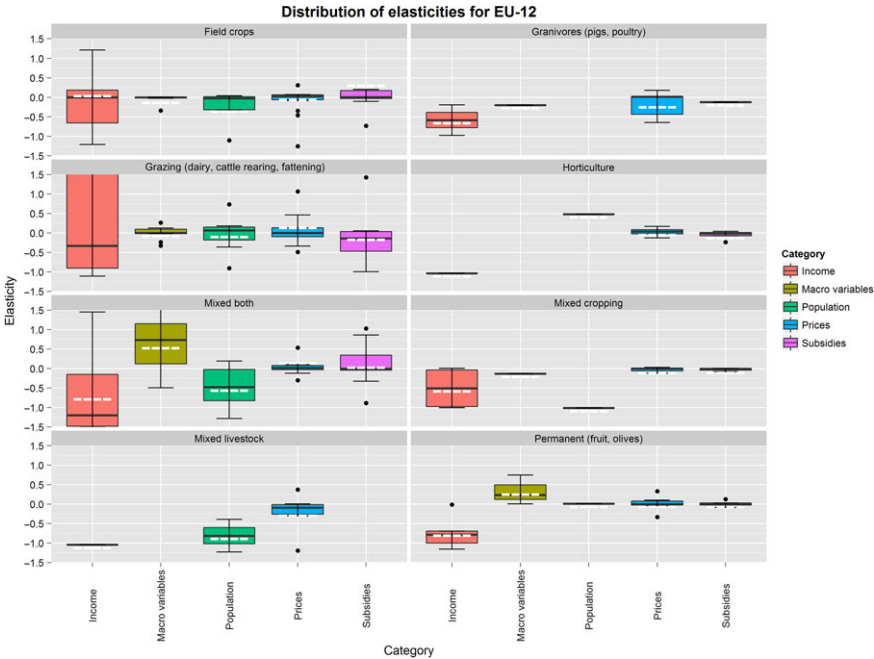
**Fig. 7.** Distribution of elasticities for EU-15 for variable categories and for all farm types across NUTS 2 regions.

*Source:* Authors' own compilation. Values for outlier elasticities are left out for presentation reasons. Mixed livestock are not considered (see footnote 16).

because, as argued in Section 2.3, the share of the farm group may increase even if the utility decreases. As the magnitude of the effect depends on the development of all farm group shares, as shown above, we have simulated the elasticities of the statistically significant variables driving farm structural change. However, a comparison of our results with the literature findings turned out to be cumbersome, as many of the existing studies neither consider farm group shares nor report elasticities.

In Appendix A.3, Tables A.2 and A.3, we attempt to report the number of variables driving structural change based on their impact on elasticities simulated by country and farm group, respectively. We have disaggregated the category of population variables into age of farmers and population density; the category of prices into input and output prices and the category of macro variables into unemployment rates, GDP growth rate and interest rate. This disaggregation allows us to better differentiate between the drivers of farm structural change. The variables most frequently reported over the countries and farm groups in the EU-15 and EU-12 can be identified and compared to the most relevant variables driving structural change considered in the literature.

Both tables show that output prices, income and subsidies are the most frequent drivers of farm structural change in the EU-15 and EU-12, as they are



**Fig. 8.** Distribution of elasticities for EU-12 for variable categories and for all farm types across NUTS 2 regions.

*Source:* Authors' own compilation. Values for outlier elasticities are left out for presentation reasons.

found statistically significant in most countries. The same is valid for farm groups across the countries, which can be partially explained by a particular relationship present between certain variables. For example, the GDP growth rate and interest rate variables show the same pattern, both for countries as well as for farm groups. Unemployment rates play a more prominent role in the EU-15 and age and population density are found statistically significant only in around half of countries, both in the EU-15 and EU-12. All these variables were found in the literature to be important drivers of farm structural change (e.g. Hallam, 1991; Goddard *et al.*, 1993; Harrington and Reinsel, 1995; Gebremedhin and Christy, 1996; Key and Roberts, 2006).

## 6. Conclusions

In this paper, we analyse the drivers of farm structure across regions and time in EU agriculture. We adopt a novel analytical framework – the MCI model – to analyse farm structural change following the theoretical framework developed for explaining market shares in the marketing literature. The advantage of this approach compared to the often-applied Markov analysis is the reduced number of parameters to be estimated, as only ‘net’ changes in each farm group are considered, rather than bilateral transitions between all

farm groups. The increased parsimony of the model specification allows us to better identify the effect of various drivers on farm structural change represented by changes in farm group shares. Another significant contribution of the paper is the application of the approach to all EU-27 countries using FADN data for the period 1989–2013. This comprehensive analysis offers the opportunity for an unprecedented comparative analysis of farm structural change across the EU. The scale and possibility of automation of the approach also opens up the possibility of incorporating farm structural change into ex-ante policy impact analysis linking at a larger scale – something often demanded but still rarely done in CAP assessments.

We define farm groups at the regional level by combining the production specialisation and size class characteristics of farms. Overall, we consider eight production specialisations and two size classes, generating a maximum of 16 ( $8 \times 2$ ) farm groups in a NUTS 2 region. To identify the drivers affecting farm structural change, we regress for each farm group and country the annual observed farm group share over seven types of explanatory variables at the NUTS 2 unit of observation: prices, population, subsidies, income, a dummy for decoupling, macroeconomic variables and natural conditions.

The results show that the largest share of the variance of farm group shares across regions and time is explained by past farm group shares, indicating the importance of historic specialisations over longer periods. At the EU level, lagged farm group shares explain approximately 36 per cent of the total variance of farm group adjustment. However, there is a sharp difference between old and new Member States. New Member States (EU-12) tend to have a more dynamic farm structure. Past farm group shares explain almost 52 per cent of farm structural change in the EU-15, while in the EU-12, its contribution is approximately 19 per cent. This difference could be attributed to the more pronounced structural changes taking place in the EU-12 due to their recent EU accession and ongoing transition process.

The results further suggest that, in new Member States, other drivers, such as subsidies, prices, macroeconomic and population variables, play a more prominent role in driving farm structural change compared to in old Member States. Indeed, subsidies explain 10 per cent of the variance in farm group shares in the EU-12 compared to 5 per cent in the EU-15, which seems to suggest that future CAP reforms may have a stronger impact on the development of farm structure in the new Member States and to a lesser extent in old Member States. Similarly, macroeconomic and population variables contribute to the explanation of farm share changes by 7 and 4 per cent in the EU-15 compared to 11 and 8 per cent in the EU-12. Consequently, ongoing macroeconomic developments, alongside population developments, explain relatively more changes in farm structure in new Member States compared to old Member States.

Contrary to our expectations, only relatively small impacts of input and output prices on farm structural change in the EU could be identified. They jointly explain structural change by 8 per cent in the EU-15 and 20 per cent in the EU-12. These relatively small effects could be due to included income variables capturing part of the price effects as well as the merely short-term

consideration of price fluctuations in the model. Income variables explain approximately 4 per cent and 9 per cent of farm structural change in the EU-15 and EU-12, respectively. Hence, the combined importance of income and price effect explaining past farm structural change is 12 per cent in the EU-15 and 29 per cent in the EU-12.

As expected, the estimated results show that natural conditions are important determinants of farm structure in the EU. They explain approximately 16 per cent of farm structure variation in the EU-15 and EU-12 across regions and time and appear to be equally important in both the EU-15 and EU-12. This is in line with expectations that farming structures are significantly determined by natural conditions, which determine the comparative advantage of various farm specialisations across EU regions.

To further analyse the importance of various drivers of structural change, we have computed elasticities representing the response of farm group shares to shocks introduced through explanatory variables. Here, we have considered only the time-varying variables related to the category of macroeconomic variables, population, prices, subsidies and income. The results suggest that farm group shares are the most elastic with respect to income variables followed by macro variables.

The elasticities showed a very heterogeneous picture across farm groups in all EU countries. For some elasticities, counterintuitive negative income elasticities for some farm groups and regions may be explained by four factors: first by production diversification with higher income levels even in the absence of overall farm group expansion. Second, decreasing average net value added per hectare could be attributed to expansion of total agricultural land. Third, the regional share of a farm group may remain unchanged while the agricultural area used to maintain status quo decreases due to productivity growth. Fourth, the income measure from the FADN represents factor income, rather than net profits.

Our results are subject to several limitations. First, our estimates may be affected by regional heterogeneity in social capital and formal and informal land market institutions, which we were not able to fully control for. These factors may play a prominent role in determining the functioning of rural markets; as a result, competitive pressures may be distorted and structural adjustments might not take full effect, which may partially explain the relatively high persistence of farm structures revealed by our analysis. In particular, land markets in some EU countries (e.g. France, the Netherlands, Poland, and Belgium) are heavily regulated, which may restrict farm adjustments. Land regulations may affect land size adjustment in particular, as they tend to distort land relocation among farms (Ciaian, Kancs and Swinnen, 2010; Swinnen, Van Herck and Vranken, 2014). Second, some EU regions show inconsistent dynamics of farm group development in the FADN data, which may have affected the farm structure evaluation over time and its statistical analysis. A country-specific rather than unique EU-27 farm group stratification could possibly better account for specific farm structures in more country-targeted analyses and would lead to a higher model fit for the specific farm groups. Finally, in this paper, we have focused on farm structural

change related to farm group shares of different production specialisations and sizes in EU regions. We did not analyse the number of farms (total and for each group), which is another key element of farm structural change. This lack of analysis could be remedied by making a separate prediction of the total number of farms (for example, see Jongeneel, 2014, 2015) and combining this with the MCI shares to calculate the evolution of farm numbers in each farm group. Another approach would be to consider farms that exit the sector in the estimation beside active farms, which is derived as the difference between the maximum number of active farms in the time series and the number of active farms in a particular year. Despite these limitations, the paper has illustrated the application of a novel approach to studying farm structural change and, in particular, it has provided a comprehensive perspective on the key drivers of farm structural change in the EU.

### Supplementary data

Supplementary data are available at *European Review of Agricultural Economics* online.

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## Appendix A

### A.1 The derivation of the estimation procedure of the differential effects MCI model

In this Appendix, we show the estimation procedure of the simple effects MCI model and switch later to the differential effects MCI model that we have applied in this paper.

Based on Nakanishi and Cooper (1982) and Cooper and Nakanishi (1988: 26–31, 108–110 and 128–130) and given the equations (2) and (3), the following equation of the simple effects MCI can be established (see Nakanishi

and Cooper, 1982: equation 2 and Cooper and Nakanishi, 1988: 26, equation 2.7):

$$s_i = \frac{e^{(\alpha_i)} \prod_{k=1}^K f_k(X_{k,i})^{\beta_k} v_i}{\sum_{j=1}^M e^{(\alpha_j)} \prod_{k=1}^K f_k(X_{k,j})^{\beta_k} v_j} \quad (\text{A.1})$$

where the farm group share  $s_i$  depends on the utility of farm group  $i$  relative to the sum of the utility of all farm groups,  $X_{k,i}$  is the  $k$ th explanatory variable of farm group  $i$ ,  $\beta_k$  is the coefficient measuring the influence of the  $k$ th explanatory variable,  $\alpha_i$  is the intercept for farm group  $i$ ,  $f_k$  is the positive, monotone transformation of  $X_k$  and  $v_i$  are the error terms.

Equation (A.1) produces non-negative market shares that sum up to one and may be transformed into a linear form in the parameters by taking the logarithm of both sides (see Cooper and Nakanishi, 1988: 28–29):

$$\log s_i = \alpha_i + \sum_{k=1}^K \beta_k \log X_k + \log v_i - \log \left\{ \sum_{j=1}^m \left( \alpha_j \prod_{k=1}^K X_{k,j}^{\beta_k} v_j \right) \right\} \quad (\text{A.2})$$

If we sum up equation (A.2) over  $i$  ( $i = 1, 2, \dots, M$ ) and divide by  $M$ , we get (see Cooper and Nakanishi, 1988: 29):

$$\log \tilde{s} = \bar{\alpha} + \sum_{k=1}^K \beta_k \log \tilde{X}_k + \log \tilde{v} - \log \left\{ \sum_{j=1}^m \left( \alpha_j \prod_{k=1}^K X_{k,j}^{\beta_k} v_j \right) \right\} \quad (\text{A.3})$$

where  $\tilde{s}$ ,  $\tilde{X}_k$  and  $\tilde{v}$  are geometric means of  $s_i$ ,  $X_k$  and  $v_i$ , respectively. Subtracting equation (A.3) from equation (A.2) gives (see Cooper and Nakanishi, 1988: 29):

$$\log \left( \frac{s_i}{\tilde{s}} \right) = \alpha_i^* + \sum_{k=1}^K \beta_k \log \left( \frac{X_{k,i}}{\tilde{X}_k} \right) + v_i^* \quad (\text{A.4})$$

where  $\alpha_i^* = (\alpha_i - \bar{\alpha})$  and  $v_i^* = \log(v_i/\tilde{v})$ . Equation (A.4) is now linear in the parameters and is called the 'log-centring' transformation of  $s_i$  (see Cooper and Nakanishi, 1988: 29).

Equation (A.4) can also be written as:

$$\log(s_i^*) = \alpha_1 + \sum_{j=2}^M \alpha_j' d_j + \sum_{k=1}^K \beta_k \log X_{k,i}^* + \varepsilon_i \quad (\text{A.5})$$

where  $s_i^* = (s_i/\tilde{s})$ ,  $X_{k,i}^* = X_{k,i}/\tilde{X}_k$  and  $\varepsilon_i = v_i^*$ . This is in line with the formulation in Nakanishi and Cooper (1982: equation 10). The intercept  $\alpha_1$  is set as arbitrary and the remaining farm group intercepts are  $\alpha_i = \alpha_j - \alpha_1$  for ( $i = 2, 3, \dots, M$ ) and a dummy variable  $d_j$ , which is equal to 1 if  $j = i$  and 0 otherwise.

If we let  $\hat{y}_i^*$  be the estimate of the dependent variable of equation (A.5), we can use the so called ‘inverse log-centring’ and obtain (see Nakanishi and Cooper, 1982: equation 11):

$$\hat{s}_i = \frac{\exp(\hat{y}_i^*)}{\sum_{j=1}^M \exp(\hat{y}_j^*)} \quad (\text{A.6})$$

which gives us an estimate for each farm group share  $i$ .

According to Cooper and Nakanishi (1988: 109) equation (A.5) can be extended by an additional index  $t$  (time). For our example, we would add the time dimension as our farm group shares are observed over time. This gives us the following equation (Cooper and Nakanishi, 1988: 109 equation 5.7):

$$s_{i,t}^* = \alpha_1 + \sum_{j=2}^M \alpha_j' d_j + \sum_{k=1}^K \beta_k X_{k,i,t}^* + \varepsilon_{i,t}^* \quad (\text{A.7})$$

where  $s_{it}^* = \log(s_{i,t}/\tilde{s}_t)$  with  $\tilde{s}_t$  the geometric mean of  $s_{i,t}$  and ( $i = 1, 2, \dots, M$ ),  $X_{k,i}^* = \log(X_{k,i,t}/\tilde{X}_{k,t})$  with  $\tilde{X}_{k,t}$  the geometric mean of  $X_{k,i,t}$  and  $\varepsilon_i^* = v_i^*$ .<sup>19</sup>

Equation (A.7) can be re-transformed to the following formulation:

$$\log\left(\frac{s_{i,t}}{\tilde{s}_t}\right) = \alpha_1 + \sum_{j=2}^M \alpha_j' d_j + \sum_{k=1}^K \beta_k \log\left(\frac{X_{k,i,t}}{\tilde{X}_{k,t}}\right) + \varepsilon_i^* \quad (\text{A.8})$$

which in turn can be reformulated as (see Nakanishi and Cooper, 1982: equation 7):

$$\log s_{i,t} = \alpha_1 + \sum_{j=2}^M \alpha_j' d_j + \sum_{k=1}^K \beta_k \log X_{k,i,t} + \log \tilde{s}_t - \sum_{k=1}^K \beta_k \log \tilde{X}_{k,t} + \varepsilon_i^* \quad (\text{A.9})$$

According to Nakanishi and Cooper (1982: equation 8), we can let:

$$\gamma_t = \log \tilde{s}_t - \sum_{k=1}^K \beta_k \log \tilde{X}_{k,t} \quad (\text{A.10})$$

where  $\gamma_t$  is independent of farm group  $i$ . Nakanishi and Cooper (1982: appendix) show that given equations (A.9) and (A.10), the regression equation can be formulated without the log-centring transformation that yields the equation, which uses the non-transformed data (see also Cooper and Nakanishi, 1988: 110 equation 5.9):

<sup>19</sup> Cooper and Nakanishi (1988) changed the way they treated the error. In their article at the beginning, the error was part of the multiplicative function (see p. 26 equation 2.7) whereas later in the article, the error was part of the exponentiation with the intercept  $\alpha_i$  (see p. 103 equation 5.1). To our knowledge, this difference has no effect on the estimation of  $\alpha_i$  and  $\beta_k$ .

$$\log s_{i,t} = \alpha_1 + \sum_{j=2}^M \alpha_j' d_j + \sum_{j=u}^T \gamma_u D_u + \sum_{k=1}^K \beta_k \log X_{k,i,t} + \varepsilon_{i,t} \quad (\text{A.11})$$

where dummy variable  $D_u$  take the value 1 if  $u = t$  and 0 otherwise. With this formulation there is no need for pre-processing of the data via log-centring.

The equation (A.11), which is the regression formulation of the simple effects MCI model can be easily extended to the differential effects MCI model. According to Cooper and Nakanishi (1988: 128 equation 5.13), from (A.11) and our equations (2) and (3) the following dummy regression formulation describes the differential effects MCI model (see Cooper and Nakanishi, 1988: 129, equation 5.17):

$$\log s_{i,t} = \alpha_1 + \sum_{j=2}^M \alpha_j' d_j + \sum_{j=u}^T \gamma_u D_u + \sum_{k=1}^K \sum_{j=1}^M \beta_{k,i} d_j \log X_{k,i,t} + \varepsilon_{i,t} \quad (\text{A.12})$$

in which the sum of the dummy variable  $d$  over  $j = 1, 2, \dots, M$  is added in the 4th summand of equation (A.11),  $d_j$  is one if  $i = j$  otherwise 0, as well as  $\beta_{k,i}$  is the coefficient measuring the influence of the  $k$ th explanatory variable on utility of farm group  $i$ .

In our paper, we want to analyse differential effects of many explanatory variables on each farm group. Therefore, we are likely estimating a lot of explanatory variables and in order to do not lose too many degrees of freedom, we drop the time dummy variable from our model and hence, our final estimation model of the differential effects MCI model has the following form:

$$\log(s_{i,t}) = \alpha_1 + \sum_{j=2}^M \alpha_j' d_j + \sum_{k=1}^K \sum_{j=1}^M \beta_{k,i} d_j \log(X_{k,i,t}) + \varepsilon_{i,t} \quad (4)$$

## A.2 Example of the calculation of the transition matrix between SGM and SO classification of the farms

To extend the classification for SO before 2004, one should re-classify the population and the FADN sample. This is only feasible when both the FADN and the FSS data are available. Unfortunately, we have no access to the FSS micro data. To overcome this problem, a transition probability matrix is calculated based on the time span for which both classifications, the SO and the SGM, are available. Based on this data, we derive the probability that a farm with a certain SGM class falls into a specific SO class. The probability matrix multiplied with the weighting factors therefore defines the share of represented farms in the SGM 13 classification falling into the corresponding 20 SO class. The transition matrix is presented in Table A1. The table reads as follows: 80.5 per cent of the farms between 2004 and 2009 with the SGM class 13 (specialised cereals, oilseed and protein crops) were

**Table A1.** Transition of SGM to SO classification for Germany

	SGM_13	SGM_14	SGM_20	SGM_31	SGM_32	SGM_34	SGM_41	SGM_44	SGM_50	SGM_60	SGM_45	SGM_70	SGM_80
SO_15	0.805	0.040								0.001			0.000
SO_16	0.051	0.776						0.001		0.029			0.012
SO_21		0.000	0.548										
SO_22	0.000		0.290							0.004			
SO_23			0.161			0.535				0.031			
SO_35				0.990		0.007				0.005			
SO_36		0.001		0.000	0.943					0.005		0.001	
SO_38				0.003	0.009	0.422				0.001			
SO_45	0.002	0.003		0.001			0.925	0.019		0.003	0.118	0.050	0.065
SO_46	0.001	0.000						0.107			0.505	0.022	0.072
SO_47	0.001				0.005		0.067	0.045			0.316	0.008	0.022
SO_48		0.006						0.813			0.007	0.000	0.015
SO_51	0.001	0.003		0.001			0.001		0.892		0.004	0.140	0.251
SO_52		0.000							0.095		0.000	0.011	0.009
SO_53									0.008			0.005	0.005
SO_61	0.001	0.005	0.001	0.005	0.031	0.012				0.414			0.001
SO_73	0.000	0.000					0.006	0.014		0.008	0.047	0.410	0.043
SO_74		0.001							0.005	0.079	0.001	0.308	0.033
SO_83	0.047	0.053					0.000			0.085	0.001	0.001	0.313
SO_84	0.089	0.111			0.012	0.024	0.000		0.001	0.336	0.000	0.043	0.160

Source: Own calculation based on FADN data from the EU Commission-FADN Unit.

classified in the SO class 15. The probabilities over all SO classes sum up to one. The transition matrix is calculated for each NUTS2 region using the farm weighting factor and is accordingly normalised.

The transition matrix is then applied to each farm for the years before 2004 to recover the SO share matrix. This is done by multiplying at the regional NUTS2 level the weighting factor of the sample farm with the probabilities from the transition matrix to obtain the population share belonging to the SO class. Problems with missing regional transitions are avoided by using instead the countrywide transition.

### **A.3 Detailed results regarding variables driving farm structural change**

**Table A2.** Overview of number of variables driving farm structural change per country based on the analysis of elasticities

EU aggregate	Country	Age	Population density	Unemployment	GDP growth rate	Interest rate	Input prices	Output prices	Income	Subsidies
EU-15	AT	1		1				7	2	3
	BL	1	1				4	10	6	2
	DE	1	1	2	1	3	2	9	2	1
	DK	1	2	9	1	2	10	22	9	4
	EL	2				2	1	4	2	2
	ES		1	4	1	2		3	1	3
	FI				2			4		1
	FR	2		6	3			4	3	6
	IR							3		
	IT			1		1			2	2
	NL		1	3	2	2	1	6	2	3
	PT			3		1	1	3	2	7
	SE	1	1	2				2		
	UK	1	1	3	1		1		3	5
	<i>Sum</i>	<i>10</i>	<i>8</i>	<i>34</i>	<i>11</i>	<i>13</i>	<i>20</i>	<i>77</i>	<i>34</i>	<i>39</i>
EU-12	BG	1	3		1			9	7	6
	CY			3		1	1	3	4	2
	CZ				2	1		6	6	4
	EE	1	1		1	1		3	1	2

(continued)

**Table A2.** (continued)

EU aggregate	Country	Age	Population density	Unemployment	GDP growth rate	Interest rate	Input prices	Output prices	Income	Subsidies
	HU	3	1	3	1	1	1	15	10	10
	LT	1		1				6		2
	LV						2	1	1	
	MT			3	1		1	3	1	2
	PL	1		1				5	4	3
	RO	1	3					5	3	
	SI	2						1	3	3
	SK	2	2	2	1	1	2	8	4	6
	<i>Sum</i>	<i>12</i>	<i>10</i>	<i>13</i>	<i>7</i>	<i>5</i>	<i>7</i>	<i>65</i>	<i>44</i>	<i>40</i>

Source: Author's contribution.

**Table A3.** Overview of number of variables driving farm structural change per farm group based on the analysis of elasticities

EU aggregate	Farm group		Age	Population density	Unemployment	GDP growth rate	Interest rate	Input prices	Output prices	Income	Subsidies
	Farm specialisation	Size class									
EU-15	Field crops	≤250k SO	4	3	6	4	3	4	27	9	16
	Horticulture	≤250k SO	1	1	2		1	1	1	2	3
	Permanents	≤250k SO	2	1	5	1	2	2	15	7	5
	Grazing livestock	≤250k SO	1		10	2	4	5	18	8	7
	Mixed cropping	≤250k SO						1	2		2
	Mixed both	≤250k SO	1	1	7	2	1	4	6	5	3
	Horticulture	>250k SO		1							1
	Grazing livestock	>250k SO			2	2	1		3		2
	Granivores	>250k SO	1	1	2		1	3	5	3	
	<i>All farm groups</i>		10	8	34	11	13	20	77	34	39
EU-12	Field crops	≤250k SO	1	1	2	2	1	3	8	12	7
	Horticulture	≤250k SO		1				1	3	1	4
	Permanents	≤250k SO		1	1		2		7	5	4
	Grazing livestock	≤250k SO	6	2	4	2	1	2	17	8	7

(continued)

**Table A3.** (continued)

EU aggregate	Farm group		Population Age density		Unemployment	GDP growth rate	Interest rate	Input prices	Output prices	Income	Subsidies
	Farm specialisation	Size class									
	Granivores	≤250k SO				1			5	2	2
	Mixed cropping	≤250k SO	1		1				3	4	3
	Mixed livestock	≤250k SO	1	1	1				6	1	
	Mixed both	≤ 250k SO	2	3	2	1		1	12	9	10
	Field crops	>250k SO	1	1	1				3	2	2
	Grazing livestock	>250k SO			1	1	1		1		1
	<i>All farm groups</i>		<i>12</i>	<i>10</i>	<i>13</i>	<i>7</i>	<i>5</i>	<i>7</i>	<i>65</i>	<i>44</i>	<i>40</i>

Source: Author's contribution.