Structural Change In European Agriculture

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Abstract

In this paper we analyse the drivers of farm structural change in the EU with a novel analytical framework, the Multiplicative Competitive Interaction (MCI) model. We use single farm data from the Farm Accountancy Data Network (FADN) for the period 1989-2011. Eight production specialisations and two size classes represent farm typologies at NUTS 2 regional level. The estimates indicate that initial state (path dependency) explains about 39.2% of EU farm structural change followed by natural conditions (18.3%) and subsidies and income (13.2%). Furthermore, the results suggest a more rigid farm structure in old compared to new EU Member States.

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

1   Introduction

The European Union (EU) agriculture went through 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-specialization over time. For example, the number of farms in the EU declined annually by 3.7% on average between 2005 and 2010. In contrast, the average farm size expanded by 3.8 % per year in the same period. As the farm size grows, farms tend to re-specialize into cereal cropping and grazing livestock away from permanent crops, granivores and mixed farming (European Commission, 2013b). Understanding the drivers of these structural changes in the past will help projecting 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 to prevent abandonment of agricultural production on land (European Commission, 2003).

A multitude of theoretical hypotheses are put forward in the literature to explain farm structural change. However, a comprehensive theoretical framework accounting for all major drivers of structural adjustment in agriculture is not available. Important drivers identified in the literature include, among others, technology (economies of scale) and productivity growth (Harrington and Reinsel, 1995), farm household and path dependency (Balmann et al., 2006; Zimmermann and Heckelei, 2012), input and output prices as well as macroeconomic drivers (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 et al., 2015b).

Several methodological approaches attempting to assess the importance of drivers on structural change in agriculture exist in the empirical literature. One key distinction between studies is the use of either macro or micro data. Studies using data at the macro level exploit the information of 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 (Breustedt and Glauben, 2007; Goetz and Debertin, 2001). The studies based on micro data explore farm level information to explain farm structural change (growth models: Bremmer et al., 2004; Weiss, 1999 and Sumner and Leiby, 1987). Spatial interdependencies between farms are considered by Storm et al. (2015b) to investigate the impact of direct payments on farm survival. Röder et al. (2014) and Neuenfeldt et al. (2014) analyse the impact of various socio-economic

drivers on changes in farm specialization. Some studies combine micro and macro data to make better use of the information when identifying significant drivers and performing projections (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. Foltz, 2004; Bremmer et al., 2012). Another important strand of applications analyses structural change with a Markov probability model (e.g. Huettel and Margarian, 2009). Given the typically limited number of observations, the Markov model requires some a-priori assumptions to lower the number of parameters estimated, particularly when the number of farm sub-groups is large. Several attempts were made to overcome this "degrees-of freedom" problem and include prior information or additional data solving this issue (Storm et al., 2015a, 2016; Zimmermann and Heckelei, 2012; Huettel and Jongeneel, 2011; Zepeda, 1995).

Our paper contributes to the existing literature on farm structural change in four ways. First, we propose a novel dynamic utility model accounting for the heterogeneous economic and social behaviour of farm groups at the regional level. Second, the proposed analytical framework overcomes the degrees of freedom problem of the Markov approach when micro data are not available. Third, the estimation of farm structural change (development of farm group shares) alongside two dimensions (i.e. by farm specialisations and farm size) is, to our knowledge, the first application for the EU-27 at NUTS 2[1] level.[2] And finally, we aim to identify the main drivers of farm structural change in the EU.

2   MCI model- Market share attraction approach

A challenge for the implementation of the Markov chain approach is that transition probabilities are defined between all considered farms groups potentially causing the negative degree of freedom especially when using aggregated data. This is particularly problematic when adding explanatory variables to estimate non-stationary transition probabilities as it reduces the degrees of freedom and may cause a so-called ill-posed problem with the number of estimated parameters exceeding the number of available observations (Stokes, 2006; Ben Arfa et al., 2015). To avoid this problem of dimensionality, we adopt Multiplicative Competitive Interaction (MCI) model based on the theoretical framework developed for the estimation of market share attractions in the marketing literature (Cooper and Nakanishi, 1988; Fok et al., 2002; Gocht et al. 2012). This approach requires only defining the "net" share of each farm group in total farm population, significantly reducing the number of estimated parameters and thus permits the inclusion of additional explanatory variables without causing the model to become ill-posed or underdetermined.

Market share models are extensively applied in the marketing literature to explain market shares of brands or products to investigate how they are affected by firm's own actions (e.g. marketing instruments, management choices), actions of competitors, and other factors such general economic development or policy changes (Cooper and Nakanishi, 1988; Fok et al., 2002). They rely on two fundamental hypotheses: (i) the market share of a brand or product is

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[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)
[2] Zimmermann and Heckelei (2012) analysed farm structural change in terms of transition probabilities rather than farm group shares for the EU at NUTS 2 level.

proportional to the marketing effort applied by the firm (Kotler, 1984) and (ii) consumers are attracted to different brands/products and the most attractive one gains the largest market share (Bell, Keeney and Little, 1975).

We extend this conceptual framework to farm groups distinguished by production specialization and farm size. According to Gocht et al. (2012), the farmers' choices on production activities determine the share of different farm groups on the market. Analogously to the market share hypotheses in which brands and products compete for shares of a limited market, the different farm groups compete for their share over limited agricultural resources (e.g. land, labour). Hence, following the market share hypotheses, each farm group share is proportional to the resources allocated and their efficient usage in the production process. Further, farm groups which generate most (utility for farmers and) competitive position in the market expand their market share.

In this paper we employ the differential effect model which 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 farms' shares than cereal farms' shares). According to Gocht et al. (2012), a farm group share "attraction" is proportional to the utility generated by operating farming activities of a certain type. The obtained utility level allows to derive market shares of each farm group in the total population. That is, the determinant of the farm group share in a region is defined by the utility generated from farming activities relative to the total utility obtained by all farm groups.

$$(1) \qquad\qquad s_i = \frac{U_i}{\displaystyle\sum_{j=1}^{m} U_j}$$

where i and j are farm group indices, U_i is the utility of farm group i, s_i is the farm group i share in all farm groups, m is the number of considered farm groups at NUTS 2 level.

We assume that farm size and farm specialization reflects different degrees of effectiveness in carrying out farming depending on different factors (explanatory variables) such as required investment strategies, policy measures, natural constraints or farm characteristics. For example, a region might be characterized by the following farm groups: large cereal farms and small pig fattening farms. Results might imply a positive effect of cereal price on large cereal farms and a negative one on small pig fattening farms. This means that the utility of large cereal farms increases while the utility of the pig fattening farms decreases. Consequently, we observe an increase of the share of the large cereal farms and a decrease of the share of small sized pig fattening farms according from equation (1). Note that the share of a farm group can decrease even when its utility increases. This is will occur when the absolute values of a farm group's utility increases less than for other farm groups.

According to Cooper and Nakanishi (1988, 28), market share models must comply with the two following logical-consistency requirements: (i) estimated market shares from the model are nonnegative and (ii) the sum of estimated market shares is equal to one. Two types of models fulfil these logical-consistency requirements: Multiplicative Interaction (MCI) and Multinomial Logit Models. For this study, we apply the MCI model which is formulated as a multiplicative function of explanatory variables:

$$(2) \qquad\qquad U_i = e^{(\alpha_i + \varepsilon_i)} \prod_{k=1}^{K} f_k(X_{k,i})^{\beta_{k,i}}$$

where K is the number of explanatory variables, $X_{k,i}$ is k-th explanatory variable explaining the utility of farm group i, $\beta_{k,i}$ is the coefficient measuring the influence of the k-th explanatory variable on utility of farm group i, α_i is the intercept for farm group i, f_k is the positive, monotone transformation of $X_{k,i}$ and ε_i is the specification-error term.

Nakanishi et al. (1982) have shown that the log-centering transformation of equations (1) and (2) is the numerical equivalent to the dummy regression model defined by

$$(3) \qquad \ln(s_{i,t}) = \alpha_1 + \sum_{j=2}^{m} \alpha_j' d_j + \sum_{u=2}^{T} \gamma_u D_u + \sum_{k=1}^{K}\sum_{j=1}^{m} \beta_{k,i} d_j \ln(X_{k,i,t}) + \varepsilon_{i,t}$$

where t and u are time indices, d_j is dummy variable for the farm group j (with $d_j = 1$ if j=i and 0 otherwise). We refrain from using the time dummy D_u in the equation (3) as it would significantly lower the degrees of freedom for the estimation.

We estimate the coefficients based on equation (3) and calculate the shares of the farm groups using the inverse log-centering transformation. That is, if we let $\hat{y}_{i,t}$ be the estimate of the dependent variable in equation (3), the estimated farm groups' share, $\hat{s}_{it}$, is given as follows:

$$(4) \qquad \hat{s}_{it} = \frac{\exp(\hat{y}_{i,t})}{\sum_{j=1}^{m_i} \exp(\hat{y}_{i,t})}$$

The advantage of this formulation is that the model can be estimated separately by farm group using Ordinary Least Squares (OLS). The model does not need to impose constraints on parameters to ensure that the shares sum up to one, because this condition is already satisfied by construction of the share equation (1)[3]. A further advantage is that farm group specific sets of explanatory variables can be used to specify the equation (3). This is particularly important in the presence of heterogeneous farm groups because different farm group shares (e.g. dairy farms *versus* cereal farms) may be affected by different drivers. For example, payments were granted under the CAP at some point coupled to production activities specifically relevant for certain farm groups but not for others.

3   Data

We follow the Farm Accountancy Data Network (FADN) typologies to construct farm groups. FADN is a European system of sample surveys that take place each year and collect detailed structural and accountancy data on EU farms. The FADN data is unique in the sense that it is the only source of harmonized 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 about 90% of the utilised agricultural land in the EU-27 (European Commission, 2010). The FADN data we employ in the study covers the period 1989–2011.

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[3] One should note that to use the full information contained within the given data and to properly estimate the coefficients, the values of the dependent and independent variables must be non-negative and greater than zero. If the condition is not met, a small constant of all variables must be added before the transformation.

The FADN classifies farms by production specialization (principle type of farming) and farm size (economic size class). The number of farms in each 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 8 farm specialisations and 2 size classes as provided in Table 1, meaning that in total we have 16 (8x2) farm groups. For example, farm group TF1-ESG8 includes all small farms specialised in field cropping, while farm group TF1-ESG9 includes all large farms specialised in field cropping. In similar way are constructed the remaining 14 farm groups. We define two size classes: small farms with standard output (SO) less than 250 000 Euro and large farms with SO greater than 250 000 Euro (Table 1). The principle type of farming (farm specialization) is defined in terms of dominant farm activity of the farm calculated as the relative share of SO of the dominant activity in the total farm SO (European Commission, 2010).[4]

Model variable construction

The dependent variable - *farm group share, $s_{i,t}$* - used in the estimation of equation (3) is defined as the ratio of the number of farms of a given farm group to the total farm population calculated at NUTS 2 level. Each farm in FADN is assigned a weighting factor which measures the number of farms it represents in total farm population. This weighting factor is derived from the surveys of farm population available from the FSS.[5] FSS employs the same farm typology as FADN. Hence, a farm group share is obtained as the sum of weighting factors across all farms belonging to the farm group divided by total number of farms in FSS.

We use six sets of explanatory variables (see Table 2), $X_{k,i,t}$, in our analysis: (i) prices (input and output prices), (ii) population, (iii) subsidies and income, (iv) a dummy for subsidy decoupling, (v) macroeconomic variables and (vi) natural conditions. The selection of variables is based on the literature on farm structural change. The sources of the explanatory variables are FADN, EUROSTAT, Worldbank, CAPRI, and CORINE land cover and EUGIS. 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 regional at NUTS 3 level. For example, EUROSTAT and CAPRI based variables are at country level, while EUGIS variables are at NUTS 3 level. The variables at NUTS 3 level have been aggregated at farm group and NUTS 2 level.

4   Empirical model specification

We aim to estimate the model as specified in equation (3) by regressing farm group share, $s_{i,t}$, at NUTS 2 level over the set of explanatory variables, $X_{k,i,t}$. However, to account for dynamic adjustments and path dependency in farm structures over time we also consider lagged variables alongside the contemporary effects. The adjustment of farm structures to changes in market and policy conditions is not instantaneous but may take time until full adjustment is realised. This 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 to switch costlessly and instantaneously between different production types (Zimmermann and Heckelei, 2012).

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[4] Over the whole period from 1989 to 2011 the definition of the farm typology changed from SGM (standard gross margin) to SO in 2009. Therefore, we recalculated the SO for all farms before 2004 based on the transition probability matrix of farms from SGM to SO between 2004 and 2009 where SGM and SO were both observed. A more detailed description of this procedure is available upon request.

[5] The weighting factor is derived by dividing the number of sample farms in FADN by the number of farms in the population (available from FSS) of the same classification.

For a number of explanatory variables we consider up to four lags for all variables, excluding prices and natural conditions. Prices are lagged for one year as we assume naïve price expectations of farmers. Further, to account for path dependency of the structural change, we include the lagged dependent variables (i.e. lagged farm group shares) as an additional explanatory variable as farms largely decide on the magnitude of structural adjustments based on their experience and past investments and take into account adjustment costs (Zimmermann and Heckelei, 2012). Variables describing natural conditions are time-invariant and primarily used to control for regional heterogeneity of growing conditions and suitability of agricultural production across various farm groups.

The resulting model specification used in estimation is as follows:

$$(5) \qquad \ln(s_{i,t}) = \alpha_1 + \sum_{j=2}^{m} \alpha_j' d_j + \sum_{k=1}^{K} \sum_{j=1}^{m} \sum_{r=1}^{R} \beta_{k,i,r} d_j \ln(X_{k,i,t-r}) + \varepsilon_{i,t}, \quad s_{k,i,t-r} \in X_{k,i,t-r}$$

Equation (5) implies that in total $K \times m \times R + m$ parameters needs to be estimated, where r is lag index and R is the total number of lags considered in the model.

We estimate equation (5) by OLS for each farm group and country using yearly observations across NUTS 2 regions. This results in a maximum of 16 (farm group) models per NUTS 2 region with one model for each combination of farm specialisation and size class. Note that for MS which joined EU at a latter period, the time series used in estimations are shorter (e.g. 2004 - 2011 for countries that joined EU in 2004) then for countries that joined earlier (e.g. 1989 - 2011 for countries that joined EU prior to 1989).

In order to reduce the dimension of the estimated models (in total we consider 119+4=123 variables)[6] we apply a forward selection algorithm for the selection of statistically significant variables. The algorithm is applied separately for every estimated model (farm group). Note that this approach may lead to the fact that the selected set of explanatory variables vary between the farm group models. In summary, the forward selection algorithm consists of the following two steps.

1. We loop over all 16 farm groups and run the estimation of the equation (5) by testing the statistical significance of adding additional explanatory variables into the starting model using the Bayesian Information Criterion (BIC).[7] This is repeated until the resulting model cannot be significantly improved which defines our final model.[8]
2. The farm group model are then used to estimate the farm utility and the inverse log centering transformation equation (4) is applied to obtain the estimated farm group shares across NUTS 2 regions.

5   Estimated results

As mentioned above, we estimate up to 16 models for each farm group and country. We refrain from presenting all the estimated coefficients for each country and farm group and

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[6] All the variables in Table 2 and their respective lags (119) and for each model the 4 lagged farm group shares.
[7] The starting model has only the intercept included.
[8] The number of observations per farm group model depends on the number of years and NUTS 2 regions. For instance, in Germany the maximum number of observations is 597. Thus, it would be possible to make a backward selection instead. But for other countries, the number of observations is below 123. A backward selection of the full model with all explanatory variables is not possible. Therefore we decided to make a forward rather than a backward selection for all countries.

rather report some statistics of the fit of the estimated regressions and the summary of the decomposition results of the drivers of farm structural change.

Fit of estimated regressions

The coefficient of determination (R^2) is relatively high, ranging between 92% in Portugal to almost 100% in Ireland, Estonia, Lithuania, Latvia, Cyprus and Malta. Between 32 and 98 different explanatory variables are selected per country out of which more than 50% are statistically significant at least at 10 percent significance level. The range of selected variables particularly depends on the number of observations available for a particular farm group and country. Note that the forward selection algorithm also included variables in the final model that were statistically insignificant (had a p-value larger than 10%), as long as the explanatory power of the whole model significantly improved based on the BIC criteria.

Decomposition of the estimated effects

To better identify the importance of various drives of farm structural change, we present summary results on the relative contributions of independent variables to the model's total explanatory value. We decompose the variance of the dependent variable - farm group shares - into relative contribution of each explanatory variable (see Grömping, 2015). We report the results by MS and aggregate them at EU-12, EU-15 and EU-27 levels for the aforementioned variable sets and (past) farm structure (lags of dependent variables).

Figure 1 presents the relative contribution of the explanatory variables to farm structural change in the EU-27. The past farm structure (the lagged farm group shares) itself explains most of the variance (39.2%), followed by natural conditions (18.3%) as well as subsidies and income (13.2%).

Figure 2 reveal a striking difference between EU-15 and EU-12 in contribution of various drivers to farm structural change. The main difference between EU-15 and EU-12 is the importance of path dependency (past farm structure) in explaining the evolution of farm groups. The past farm structure explains almost 50% of the farm group shares' variance in EU-15, while in EU-12 its contribution is much smaller, around 20%. In other words, these results imply a more rigid farm structure in EU-15 than in EU-12.

Natural conditions appear to be equally important in explaining farm structural change in both EU-12 and EU-15, although with some variation across individual countries. They explain about 19.3% in EU-15 and 17.1% in EU-12 of the farm group shares' variance.

Subsidies have a stronger impact on farm structural change in EU-12 than in EU-15. Subsidies and income as well as the decoupling dummy contribute by 24.8% and 14.1% to driving farm structural change in EU-12 and EU-15, respectively.

The combined macroeconomic and population drivers contribute to the explanation of farm share changes by 9.8% in EU-15 and 20.9% in EU-12. Population density explains a larger part of structural change in countries such as Denmark, Estonia, Ireland, Latvia, Malta, Sweden and Finland. Other macro variables are particularly important drivers in Estonia, Denmark, Greece, Hungary, Malta and Slovenia.

Finally, the prices explain the structural change by 7.3% in EU-15 and 17.5% in EU-12. Compared to other variables, we would expect a greater importance of prices in driving farm structures.

Figure 3 shows the variance decomposition by farm specialization. The left hand side panel presents the results for EU-15, while the right hand side panel for the EU-12. In general, there are no significantly different patterns observed between the farm specializations. The main difference is only that past farm structure has considerably stronger impact in EU-15 compared to EU-12.

6   Discussion and conclusions

In this paper we analyse the drivers of farm structural change in EU agriculture. We adopt a novel analytical framework - Multiplicative Competitive Interaction (MCI) model - following the theoretical framework developed for estimation of market share attraction model in the marketing. The advantage of this approach is that it is less data demanding compared to the usually applied Markov approach, because instead of using transition probabilities between farm classes, it exploits the "net" change of farm group shares. Hence, we do not need to observe transition between farm groups, which are not easily available for the data over a longer period. Further, the advantage of this approach is that it reduces significantly the dimensionality problem, characteristic for the Markov approach when estimating non-stationary models, and thus allows better identifying the effect of various drivers of farm structural change.

We apply the approach for all EU-27 countries using the FADN data for the period 1989-2011. We define farm groups at regional level by combining production specialisation and size class characteristics of farms. Overall, we consider 8 production specialisations and 2 size classes generating a maximum of 16 (8x2) farm groups in a NUTS 2 region. To identify the drivers affecting farm structural change, we regresses independently for each farm group the annual observed farm group share over six set of explanatory variables at the NUTS 2 regional level: prices, population, subsidies and income, a dummy for decoupling, macroeconomic variables and natural conditions.

Our estimated results indicate a strong path dependency – most of the variance is explained by the past farm structure – of farm structural development in EU indicating that farms tend to maintain specialization and/or size unchanged over longer period. At EU level, the path dependency explains about 39% of the total variance of farm group adjustment. However, there is a strong difference between old and new Member States. The new Member States (EU-12) tend to have a more dynamic farms structure than the old Member states (EU-15). The path dependency explains almost 50% of the farm structural change in EU-15, while in EU-12 its contribution is much smaller, around 20%. This difference could be attributed to the stronger structural changes taking place in EU-12 due to their recent EU accession and the ongoing transition process. The countries with the largest impact of the past farm structure (more than 70%) are Italy, France and Germany where the farm structure is quite rigid and insensitive to changes in external drivers. From EU-12, only Poland has a comparable rigid farm structure to EU-15 average. The most dynamic farm structure seems to have Malta, Latvia, Slovenia, Denmark and Estonia.

As expected, the estimated results show that natural conditions are important determinants of farm structure across EU regions. They appear to be equally important in explaining farm structural change in both EU-15 and EU-12, overall explaining about 19.3% in EU-15 and 17.1% in EU-12 of the farm structure. This is in line with our expectations that farming structure is significantly dependent on the natural factors such as climate, slope and vegetation period. The natural factors reflect the diversity of growing potential across regions in the EU and thus determine comparative advantage of various farm specializations.

The main economic drivers of farm structural changes appear to be subsidies and income as well as macroeconomic variables. Both drives have a stronger impact on farm structural change in EU-12 than in EU-15. Subsidies and income as well as dummy for decoupling contribute by 24.8% and 14.1% to driving farm structural change in EU-12 and EU-15, respectively. Subsidies have a stronger impact on farm structural change in EU-12 than in EU-15. For macroeconomic variables, they contribute to the explaining the farm share changes by 9.8% in EU-15 and 20.9% in EU-12.

Contrary to our expectations, the estimations indicate a relatively small impact of input and output prices on farm structural change. The prices explain the structural change by 7.3% in EU-15 and 17.5 % in EU-12. This low estimated effect could be due to the fact that income variables may capture part of the price effect as well as not all price variations may induce farm structural adjustment in particular if they are of short-term duration. We have observed in the past several price peaks such as after the BSE crisis in 2000 and the agricultural commodity price spike in 2007-08. The signals of such relatively short-term shocks might not be fully translated into the farm structure adjustments.

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 in our estimations due to unavailability of data. These factors may play a prominent role in determining the functioning of rural markets, as a result of which competitive pressures might be distorted and structural adjustments might not take full effect in such a setting. This may partially explain the relatively high path dependency of farm structure estimated in our paper. 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 in particular land size adjustment 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 FADN data which may have distorted the farm structure evaluation over time and thus also estimated results. Finally, in this paper we have focused on farm structural change related to the distribution of farming population between different production specializations and sizes in EU regions. We did not analyse the number of farms which is also a key element of farm structural change. The reason is that the MCI estimation approach employed in this paper cannot analyse the number of farms, only the share of farms belonging to a type within the total farm population. To obtain the number of farms, one would need to predict the total number of farms which then can be used to calculate the evolution of farm numbers in each farm group. For example, this can be estimated using a model that explains the number of farms as a function of several explanatory variables as proposed by Jongeneel (2014, 2015).

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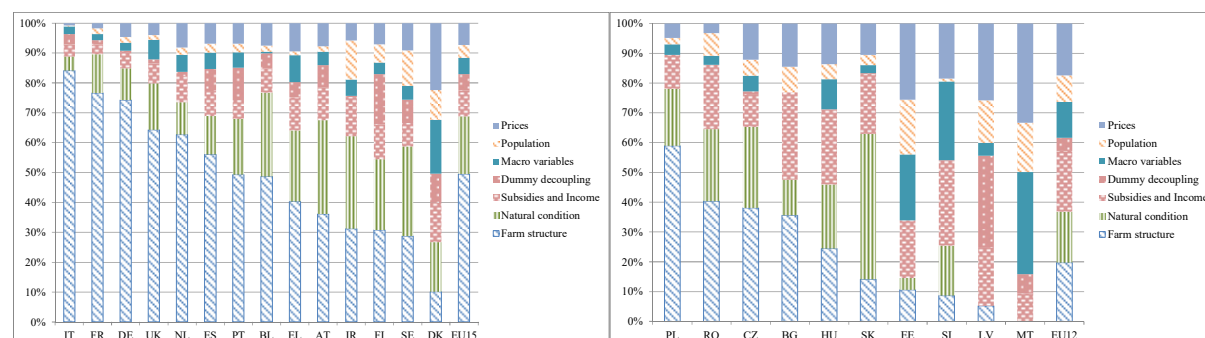
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**Figure 1: Variance decomposition for EU-27**
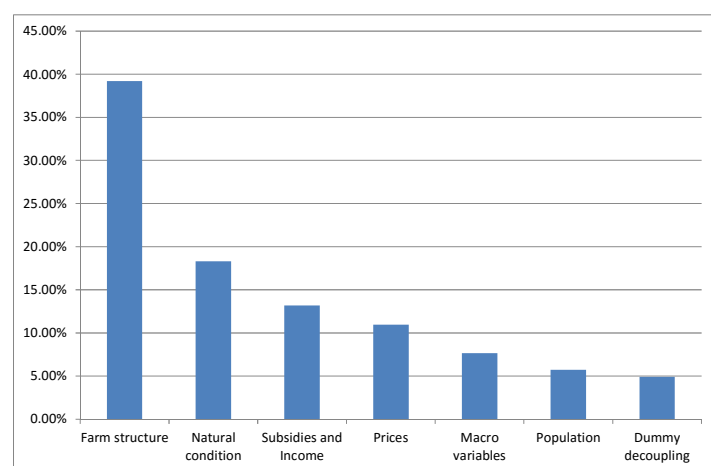
Source: Own calculation based on FADN data from the EU Commission- FADN Unit

Figure 2: Variance decomposition by country in EU-15 (left panel) and EU-12 (right panel)

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

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Figure 3: Variance decomposition by farm specialisation in EU-15 (left panel) and EU-12 (right panel)
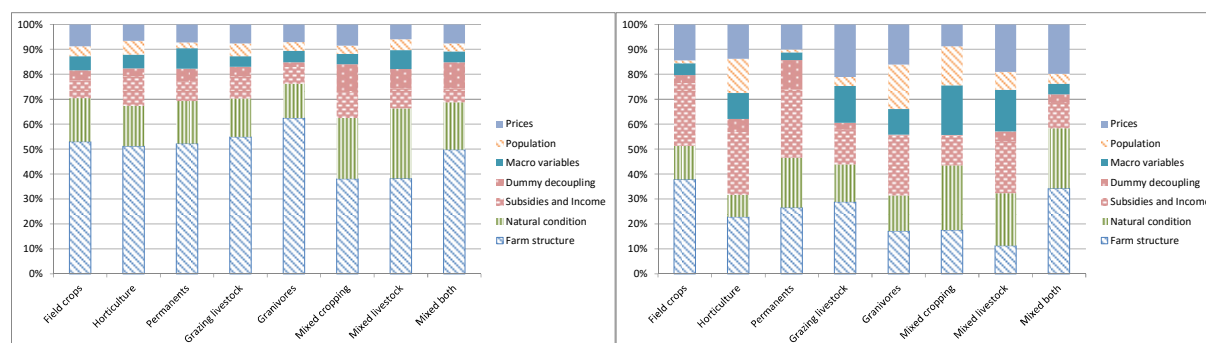
Source: Own calculation based on FADN data from the EU Commission- FADN Unit

Table 1: Farm classification

Code	Name	Description
Production specialization		
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 ornementals; 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-grazing livestock combined; various crops and livestock combined
Farm size class		
ESG8	Small farms	Farms with SO less than 250 000 Euro
ESG9	Large farms	Farms with SO more than 250 000 Euro

Note: SO=Standard output

Table 2: Overview of the variable sets and the selected variables

Variable set	Variables
Natural condition	Share of: Arable land, Artificial land, Forest and semi nat. areas, Heterogeneous agri. areas, Pastures, Permanent crops, Water bodies, Wetlands Aridity index average and standard deviation of growing degree days (5°C and 10°C threshold) average and standard deviation of vegetation period (5°C and 10°C threshold) Slope in percent and elevation in meter – both from 93m raster
Subsidies and Income	Farm net value add. per farm/UAA/AWU; Total subsidies per farm/UAA/AWU
Dummy decoupling	Dummy decoupling
Macro variables	Interest rate, GDP growth rate, Unempl. rate (total),Unempl. rate (total, female), Unempl. rate (total, male), Unempl. rate (total, age >25)
Population	Population density, Age of farm holder
Prices	*Prices at member state level*: Cereals, Oil seeds, Potatoes, Sugar beet, Vegetables, Fruits, Other industrial crops, Gras, Raw milk at dairy, Pork meat, Beef, Poultry meat, Other animals output, Sheep and goat meat, Eggs, Pharmaceutical inputs, Renting of milk quota, Fuels, Heating gas and oil, Electricity, Other inputs, Maintenance buildings, Maintenance materials, Services input, Plant protection, Seed, Other crops *Prices at NUTS 2 level*: Cereals, Other arable crops, Barley, Dairy milk, Oats, Potatoes, Rye and meslin, Eggs, Meat from Cattle, Oilseeds, Other animals, Rape seed, Product soft wheat