USING MARKET SHARE AND MULTIPLICATIVE COMPETITIVE INTERACTION MODELS TO EXPLAIN STRUCTURAL CHANGE IN THE GERMAN AGRICULTURAL SECTOR

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Abstract: *We use a Multiplicative Competitive Interaction (MCI) model, a popular approach in marketing research, to explain the change in farm specialization over time. The change in farm specialization is measured by the variations of the Standard Gross Margin (SGM) shares. The model is applied to the German Farm Accountancy Data (FADN) using the years 1990 until 2008. Therefore, a MCI model was developed using various lagged explanatory variables, evaluated using a forward selection based on log likelihood ratio test. Using an in-sample forecast the approach correctly predicts 99% of the farm specialization development.*

1. Introduction

There exists a vast amount of approaches and models that explain structural change in agriculture. Zimmermann et al. (2009) and Gocht et al. (2012) provided recently an overview. There exists a stand of literature on stationary Markov approaches and non-Stationary approaches. Furthermore, econometric models exists which are characterized by regressions on a number of explanatory variables. The regression analyses can thematically be divided into three model variants. Most of the regression models are related to analysing farm growth others are cohort analyses which concern the number of farm holders and the reasons for entering or leaving the sector. The last variant of models considers farm succession explicitly.

In this article structural change is captured by the change in farm specialization. In other words we are interested to explain the determinants why a farmer changes its specialization, e.g., from a specialized dairy to diversified mix cropping or livestock farming. The specialization is measured by the share of a given production branch on the farm's total standard gross margin (SGM). The novelty of the approach is that we use a class of well-developed models from marketing science, which has the advantage of analysing and quantifying the change in the productive orientation on a continuous scale. Socio-economic, geographical and climate variables are used as explanatory variables.

2. Market Share attraction and MCI-models to analyse structural change

2.1 *The adaptation of the MCI models to the analysis of farm specialization evolution*

Market Share and MCI-models are widely used in marketing research to estimate market shares of brands and to analyse the effects of marketing instruments (e.g. advertisement expenditure) on the market shares. The basic idea is that consumers are attracted toward different brands and the brand with highest attraction has the greatest market share (Kotler, 1984; Bell et al., 1975). The market share of each brand can be a linear, multiplicative or exponential function of the marketing instruments (Cooper and Nakanishi, 1988: 27).

We interpret the production branches of a farmer (e.g. cash crops or dairy production) also as market shares, defined by rules relating to the contribution of the production branches expressed by the partial SGM in relation to the total SGM. We argue that the different production branches compete for resources, such as labour, land and capital. The farmer will devote his resources which provide him with the highest utility. This is in our view a situation comparable to the choice of a group of consumer intending to maximize their utility by dedicating their budget to the purchase a certain mix of brands for a given product. Therefore we apply the market share concept for explaining the change of farm specialization. The shares of different farm specializations and socioeconomic variables are used instead of a brand's market share and its marketing instruments.

2.2 *General model and model specification*

We investigate the impacts when a given explanatory variable may have different effects on each farm specialization. This model approach is known as differential effect model. In the

farm specialization share case "attraction" is proportional to the utility of a given farm specialization. For example, a farmer may have the following production mix: cereals, dairy cattle and pigs. The regression estimation might imply a positive effect on cereal cropping and a negative one on pig fattening due to an increase of the cereal price. This means that the "attraction" of cereal cropping increases while the attraction of pig fattening decreases. Consequently, the farm specialization share of cereal cropping increases whereas the one of pig fattening decreases. The differential effects model can be formulated generally as follows:

$$s_i = \frac{A_i}{\sum_{j=1}^{N} A_j}, i = 1, \ldots, N, j = 1, \ldots, N, \tag{1}$$

$$A_i = \varepsilon^{(a_i + \epsilon_i)} \prod_{k=1}^{K} f_k (X_{k,i})^{\beta_{k,i}}, \tag{2}$$

where A_i is the attraction of farm specialization i, s_i is the farm specialization share of specialization i, N is the number of farm specializations of a farm. The farm specialization share is calculated as the proportion of the attraction of a certain farm specialization to the sum of the attractions of all farm specializations. $X_{k,i}$ is the value of the k-th explanatory variable with $k = 1, \ldots, K$ explaining attraction of farm specialization i, $\beta_{k,i}$ the coefficient of the influence of the k-th explanatory variable on attraction of farm specialization i, α_i is the intercept of attraction of specialization i, $f_{k,i}$ the positive, monotone transformation of $X_{k,i}$ and ϵ_i the error term. With the estimated attraction values the farm specialization share can easily be derived from Equation (1). The models must comply with the two following basic conditions: The estimated farm specialisation shares are non-negative and sum up to one. MCI models fulfil these properties and explain the attraction of the farm specialization share as a multiplicative function of the explanatory variables. To apply common linear estimation techniques, the natural log is taken.

We assume further that a farmer will determine the magnitude of his activities based on his experience in the previous years rather than based on the actual situation. Therefore, we lag all the explanatory variables by up to four years. The magnitude and direction of a farmer's modification of his productive program to a given stimulus depend on his past production program, as a change in the program might involve substantial investments. Therefore, we extend the model by lagged farm specialization shares as additional explanatory variables. Each variable, where data are available, is considered in the form of a one-, two-, three-, or four-year-lagged explanatory variable. The basic model consists of a one-year-lagged farm specialization share model. The resulting dummy regression formulation of differential effects model (Equation (1) and (2)) is written as follows:

$$\ln(s_{i,t}) = \alpha_1 + \sum_{j=2}^{N} \alpha_j d_j + \sum_{k=1}^{K} \sum_{j=1}^{N} \beta_{k,i} d_j \ln(s_{k,i,t-1}) + \epsilon_{i,t} \tag{3}$$

This equation has the time dimension t and contains dummy variables for farm specialization ($d_j = 1$, if $i = j$ and 0 otherwise); these dummy variables are required to use common linear estimation techniques. This is the basic model, in which in addition to the average effect of each farm specialization, the farm specialization shares of the previous year determine the ex-ante simulation of the amounts of each farm specialization share of each farm. For the final model, Equation (3) is extended by additional explanatory variables so that the farm specialization share is the result of the one-, two-, three-, and four-year-lagged farm specialization shares and the lagged explanatory variables.

$$\ln(s_{i,t}) = \alpha_1 + \sum_{j=2}^{N} \alpha_j d_j + \sum_{k=1}^{K} \sum_{j=1}^{N} \sum_{r=0}^{R} \beta_{k,i,r} d_j \ln(X_{k,i,t-r}) + \epsilon_{i,t}. \tag{4}$$

Furthermore each time variant explanatory variable has lags of $r = 1, ..., 4$ or $r = 2,3,4$ for the lagged farm specialization shares. The time invariant explanatory variables are not lagged $(r = 0)$.[1]

3. Data

We use the German set of FADN farms. The FADN database includes structural and financial information for each farm included in the sample. This database is a rotating sample of commercial farms and the data is extrapolated to the population based on farm specific weighting factors. For each farm and year we calculate the particular share of given group by dividing the group's SGM by the farm's total SGM. The production activities which are associated with the specialisation can be derived from the official documents defining the type of farming in FADN (EU, 2008). We aggregated several "official" specializations to reduce the amount of data to be handled (see Table 1). Even with this reduced specialization typology we can fully recover the 2-digit FADN type of farming typology.

Table 1. Definition of farm types considered for prediction

Farm specialisation (i)	Farm specialisation	Description	Type of Farming (EU, 2008)
Cereals	D_13	Cereals, Oilseed & Protein	13
Other field crops	D_14	Specialist other field crops	14
Horticulture	D_2	Horticulture	20
Permanent Crops	D_3	Permanent Crops	30
Milk	D_4_D1	Specialist milk	41
Other grazing livestock	D_4_X2	Specialist sheep and goats; Specialist cattle	42, 43, 44
Granivores	D_50	Specialist granivores	50
		Mixed farms	60, 70, 80

Source: EU, 2008 and own compilation

Table 2 lists the explanatory variables used for the estimation. The lagged specialization shares are also considered in this list. All variables were tested for being reasonably independent. We removed all variables with a Pearson correlation coefficient higher than 0.8.

Due to the log transformation in Equation (4) and in order to keep the information of the full data set, zero and negative values must be avoided. Therefore, we added a small constant (0.1) to every variable which contains zero values before the transformation. For average water balance we added 200 to avoid negative values and for average driving time to next central station we added 1.

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[1] Some of the explanatory variables are not lagged because they are time invariant. See data description for that.

Table 2. List of explanatory variables

Category	Explanatory variable	Category	Explanatory variable
Policy	1. pillar premium[1]	Natural conditions[5]	Summer temperature (°C)
	Agri-Env premium[1]		Winter temperature (°C)
	Other 2. pillar premium[1]		Precipitation (mm / a)
Prices [4]	Sugar beet[2]		% grassland on UAA (Region)
	Wheat[2]		Slope (%)
	Pork[2]		% of Natura 2000 areas
	Milk[2]		Altitude (meters)
Farm Economics	Farm Size (kSGM)	Region[5]	% Employed persons[3]
	Share of interest payments[1]		Change in employed persons[3] (%)
	Land rent (€/ha)		Commuting time to next main city (min.)
	% rented land		
	Share of grassland		Population density
	Stocking density (LU / ha)		
	SGM Shannon		Change population density[2]

[1])Relative to SGM; 2) Relative to previous year; 3) Average share on total working population, 4) Prices for durum wheat, beef meat, rape seeds and flowers were excluded in a block wise forward selection, conducted in a pre-test, 5) These variables are time invariant and have no lags.

Source: Own compilation. Data sources: FADN, EUROSTAT, BBSR, DWD, BKG, EEA.

4. Empirical implementation and results

Many farms are highly specialized and have one high share (dominant specialisation) and the remaining specialisations are rather low. In most cases the relative variation over time of the dominant specialisation is fairly small compared to the relative variation for marginal specialisations. Marginal specialisations are based only on some hectares and/or animals, which can removed or added to the production program. A percentage point change for a marginal specialisation implies a higher relative change compared to a dominant specialisation. Because the applied model considers the shares as independent observations we can reduce this effect by dividing each specialisation shares into sub-groups. We differentiated the following four sub-groups >66%, 33%-66%, 5%-33% and <5%.

To reduce the dimensions of the regression we performed a forward selection of all the explanatory variables as described in Equation (4). First, we run a model, which extends the basic model by each variable. The D-value of the log likelihood is used to identify the variable with the greatest improvement in the model fit. This variable together with the basic model is tested against the previous basic model for significance (5% level) by using the log likelihood-ratio test. The variable with the greatest improvement is added to the basic model.

The final full model has a coefficient of determination of 99% and reduces the RSS by 68% (log likelihood: 258,182; dF: 283,529) compared to our reference, for which we assume that the shares are just a function of the values observed in the previous year. In the final model most of the variance is explained by the historic farm structure (as depicted by the partial SGM) of the previous years (2-4 years before the observation to be predicted). The historic farm structure and the farm economics variables reduce the RSS by 66%, policy and prices variables by 20%, regional and natural conditions variables by 14%. Generally speaking, farm level data allows a much higher improvement of the model fit compared to information on prices and policy or regional data. However, one should bear in mind that the data set is much more heterogeneous with respect to farm level data compared to the other data domains.

5. Summary and conclusion

We showed that the MCI approach can be a useful tool for the in-sample prediction and explanation of structural change in agriculture. It could be clearly shown that the historic farm structure explains most of the variance farm specialization development. The deeper analysis also revealed that some of the estimated coefficients imply a strange reaction of the farm specialization shares with respect to some prices. The reasons can be partly attributed to peculiarities of the used data set. First, agriculture is not a very dynamic segment of the economy. Therefore, the assumption of no change or business as usual is validated by the observed time series. Second, the MCI approach assumes that the micro transitions, (i.e. type of farming) observed in the FADN sample, are somehow representative for the whole population. However, this is clearly not the case as the dynamic subset of farms is automatically removed from the FADN sample due to the sampling protocol. All these problems ask for caution when it comes to interpretation of the coefficients derived in the regressions for the explanatory variables. Temporal multicollinearities seem to be a reason for some strange reactions. With regard to potential further research the following issues should be highlighted. First, solving the data constraints issues (e.g. rotating sample, representativeness) which derived from the use of the sub-sample in FADN by using the micro-FSS data. Second, additional research could also be done by applying the MCI approach for farm specialization shares at regional level. In contrast to the farm level case, farm specialization changes at regional level are likely to be smaller and less erratic and hence, better to estimate. But it has to be investigated, how the behavioural entity of observation (region instead of farm) can be interpreted. The shrinking number of observations at regional level has also to be considered.

6. References

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