How Spatial Pricing Affects Cooperative Members' Switching Decisions

Tim Viergutz*[1], Nana Zubek[2] and Birgit Schulze-Ehlers[1]

[1]University of Goettingen, Department of Agricultural Economics and Rural Development, Platz der Goettinger Sieben 5, 37073 Goettingen, Germany

[2]University of Kiel, Department of Agricultural Economics, Wilhelm-Seelig-Platz 6, 24118 Kiel, Germany

*Corresponding author: tim.viergutz@agr.uni-goettingen.de

Paper prepared for presentation at the 149th EAAE Seminar 'Structural change in agri-food chains: new relations between farm sector, food industry and retail sector'
Rennes, France, October 27-28, 2016

Abstract

Structural change at both farmer and cooperative level has significantly altered the vertical relationships between them, with increased member switching activities resulting in negative economic impacts on cooperatives. This paper uses spatial panel modelling in combination with simulation approaches to identify the impact of prices and cooperative member density as well as competitors' organizational form, production quantity and production growth on members' switching decisions. With a unique data set we can show that these indicators determine switching decisions. Additionally, findings hint at the relevance of social interaction for members' switching decisions.

Keywords: agricultural cooperatives, switching behaviour, member loyalty, spatial price incentives, spatial interaction

1. Introduction

In the European Union, farmers' cooperatives hold substantial market shares (40% on average) and in some member states (e.g. Germany) almost every farmer is a member of a cooperative (Bijman, et al., 2012). However, in recent years, deteriorated farmer-coop relationships and consequentially higher switching activities of members, threaten their financial stability (Fulton and Giannakas, 2001; Lang and Fulton, 2004; Nilsson, Svendsen and Svendsen, 2012).

This development stimulated increased research into the determinants of farmer commitment to and active participation in cooperatives (Barraud-Didier, Henninger and El Akremi, 2012; Bhuyan, 2007; Cechin, et al., 2013; Morfi, et al., 2015; Nilsson, Svendsen and Svendsen, 2012; Ollila, 2011). Key results refer to a considerable relevance of non-monetary arguments for the stability of buyer-supplier relationships in general (Gyau, Spiller and Wocken, 2011; Schulze, Wocken and Spiller, 2006), and cooperative membership specifically (Hernandez-Espallardo, Arcas-Lario and Marcos-Matas, 2013; Nilsson, Svendsen and Svendsen, 2012). Particularly, the relevance of social capital, trust, and feelings of belonging have been addressed (Barraud-Didier, Henninger and El Akremi, 2012; Feng, et al., 2011; Hansen, Morrow Jr and Batista, 2002; Mazzarol, 2012; Osterberg and Nilsson, 2009). In relation to investor-owned firms, cooperatives have been found to still have some advantages with respect to supplier bonding: Some scholars found that cooperatives still are preferred trading partners (James Jr. and Sykuta, 2006; Roe, Sporleder and Belleville, 2004) and explain this outcome particularly with a higher level of trust, which is due to the frequently discussed advantages resulting from the ownership and governance structure (Feng, Friis and Nilsson, 2016; Hernandez-Espallardo, Arcas-Lario and Marcos-Matas, 2013; Hess, Lind and Liang, 2013).

However, Feng et al. (2016) can show that with increasing size of cooperatives, the often emphasized positive impact of social capital is weakened. Given the ongoing structural change at processor level (Fulton and Giannakas, 2001) and a reduced political support for the agricultural sector in Europe, we assume that the long-standing arguments of social cohesion and other social factors driving cooperative member loyalty, is decreasing in relation to monetary incentives.

The relevance of prices for member loyalty can be assumed to be of even higher research interest, as the "regional principle", which long informally prohibited competition among cooperatives in the same area, is no longer practiced (Fousekis, 2011; Zeuli and Bentancor, 2005), while cooperatives are often bound to a uniform or equal pricing policy justified by the core cooperative principle of "equality" (Kyriakopoulos, 2000). This prohibits a discrimination of prices to react to competitors' prices in regions of stronger competition, although it might be economically beneficial. Overall, this underlines the need for understanding the effects of pricing on farmers' switching behaviour and consequential membership dynamics.

However, previous research has not focussed much on prices. If the above mentioned studies include monetary variables, they usually rely on price perceptions instead of real prices and price relations among competitors. While this seems appropriate from a behavioural science perspective, which acknowledges heterogeneous perceptions of the same event by different individuals, the approach is at the same time prone to problems such as measurement bias, and difficult to use as a decision support in member loyalty programmes or other efforts of cooperatives to retain members.

Furthermore, the studies usually use cross-sectional survey data and therefore have to rely on stated intentions or behaviours which extends the potential biases to problems of common method variance (Podsakoff, et al., 2003) and attitude-behaviour gap (Ajzen and Fishbein, 2005), limiting the predictive power of respective models. Overall, we conclude that studies so far widely lack objectively measurable determinants of farmers' switching decisions. Moreover, the use of cross-sectional instead of panel data implies obvious limitations in the explanation of events whose occurrence as well as development require a time-series design.

In this paper, we specifically try to shed light on the role of spatial price differences in determining farmers' switching decisions. By using a unique data set of spatiotemporally referenced switching decisions of members of a large European agricultural cooperative, we address the above mentioned limitations of prior empirical studies.

The paper is organized as follows. After explaining our notion of farmers' switching decisions, we discuss how geographic space relates to actual switching decisions in the supply base. Based on that rationale we formulate hypotheses regarding the relationship between objective indicators, such as spatial prices, and actual switching decisions in the supply base. Subsequently, these hypotheses are tested against a data set comprising actual switching decisions in a large European dairy cooperative over seven years and complemented by spatial pricing information as well as regional indicators on local market structures. To achieve this, spatial panel modelling in combination with simulation approaches is used. Finally, the results are discussed and recommendations for future research are provided.

2. Spatial effects on farmers' switching decisions

We define a farmer's switching decision as his defection to another buyer. Given rather long periods of notice in cooperatives, we are dealing with situations where farmers irrevocably decide to terminate the business relationship with their current buyer in order to trade with another buyer in a more or less distant future point in time.

Assuming rational-decision making, farmers switch the business partner if the expected utility of dealing with another business partner exceeds the expected utility of maintaining the business relationship (Pascucci, Gardebroek and Dries, 2011). Since farmers' defecting the cooperative weakens the financial stability and input security (Fulton and Giannakas, 2001; Nilsson, Svendsen and Svendsen, 2012), it is in a cooperative's best own interest to retain the member base. Hence, in order to stay competitive, the cooperative has to satisfy its' members interests better than any outside option (Ortmann and King, 2007).

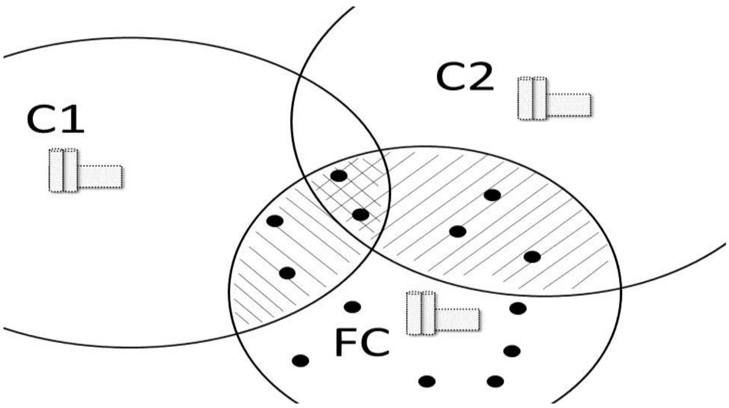
In general, the members of agricultural marketing cooperatives are interested in maximizing their monetary revenues generated through the business relationship (Tennbakk, 2002). The fundamental idea is to create countervailing power through collective action in purchasing and processing was to achieve more competitive prices (Fulton, 1999; Hansmann, 1996) and thus to increase their profits. Since the cooperatives' surplus income is distributed to members in proportion to their use, the profit-maximizing farmer seeks to maximize the returns of the products supplied to the cooperative, which is determined by the prices paid for the input (LeVay, 1983; Ortmann and King, 2007). From this perspective, the farmers' motivation to create and support cooperatives is solely based on the underlying incentive to maximize their monetary revenues aiming at advantageous prices paid by their cooperative. Hence, the competitiveness of prices paid by the cooperative is of crucial importance for the satisfaction and commitment with the cooperative (Fulton, 1999; Hernandez-Espallardo, Arcas-Lario and Marcos-Matas, 2013; Lang and Fulton, 2004).

A major advantage of focusing on prices and price relations is that they are objective and – in agriculture – often readily available indicators for the relative attractiveness of doing business with different business partners. Farm gate price comparisons are supposed to create market transparency and are often considered by farmers (Lehmann, Dannenberg and Kulke, 2013).

However, such price comparisons have to be put into perspective taking into account spatial effects: Not only can actual switching options be narrowed by economically feasible transport distances (Rogers and Sexton, 1994), but the distance also affects the actual price outcome for the farmer. The spatial dimension thus plays an important role for the analysis of agricultural markets (Graubner, et al., 2011). The cooperative supplier base and the factors influencing a farmer's switching decision should therefore be considered from a spatially embedded perspective. Previous studies so far have considered farmers perceived switching costs, or structural bonds, and found some small but significant effects on switching intentions (Schulze, Wocken and Spiller, 2006). However, to our best knowledge, no objective indicators, such as actual distances, have been taken into account.

Figure 1 illustrates a simplified perspective on a spatially embedded cooperative supplier base, where the farming suppliers (black dots) of a focal cooperative (FC) are geographically distributed in its catchment area. Catchment areas are defined by the maximum economically reasonable distance of transportation to processor sites, and depicted by circles around the processing sites. Next to the FC, two competitors (C1 & C2) embedded in their respective catchment areas are depicted.

Figure 1: Simplified scenario of a spatially embedded supplier base



Farmers residing in the non-overlapping parts of the catchment areas are not located in favorable distance for other processors. Consequently, we assume that FC members face different switching options dependent on their localization and therefore also face different incentives to switch the business partner. This scenario seems realistic because uniform pricing, where the buyer pays the full costs of transportation from the farm to the processing facility resulting in uniform prices across the catchment area, is rather common in practice (Durham, Sexton and Song, 1996; Graubner, et al., 2011; Greenhut, 1981).

Besides the above described spatially determined monetary incentives to switch, the spatial location of the farmer can be assumed to take up further factors indirectly influencing switching decisions. Factors such as the farmers' input factor markets (namely, land), farm characteristics as well as further factors influencing production are likely heterogeneously distributed across space (Kitchin and Thrift, 2009). This heterogeneity in distribution of factors across space may be approached via the notion of spatial autocorrelation. According to Anselin and Berra (1998: 241), "spatial autocorrelation can be loosely defined as the coincidence of value similarity with locational similarity". We speak of positive spatial autocorrelation when either high or low values for a random variable tend to cluster in space, and of negative spatial autocorrelation when locations tend to be surrounded by locations with very dissimilar values. Positive autocorrelation is by far the more intuitive (Anselin and Bera, 1998) and it is much more common in nature (Kitchin and Thrift, 2009), but negative autocorrelation does exist (Plant, 2012). Assuming positive spatial autocorrelation underlying the spatial heterogeneity of factors indirectly affecting a farmer's switching decision, farmers located close to each other not only face similar price incentives, but also similar other relevant factors determining the switching decision, such as dealing with the same cooperative personnel, having similar levels of land and other input prices, or the like. Hence, we assume that the relative spatial location of farms implicitly takes up the influence of other relevant variables as well.

Following this way of thinking, spatial aggregation of a FC's membership base into spatial entities implies that farmers located in an area (explicitly and implicitly) face similar switching incentives. Such aggregation has the additional advantage that it allows the use of areal data regarding the group composition or other factors associated with the respective spatial entity, which induces potential to account for other contextual factors influencing the switching decisions. It is important to note that aggregation in spatial units may imply problems regarding zoning and scale effects (Dusek, 2004). However, we argue that aiming at a deeper understanding of the spatial context and to acknowledge the existence of other (non-economic) factors influencing switching decisions compensates for such potential drawbacks.

3. Hypotheses

In this chapter, hypotheses are formulated based on spatial aggregates given the considerations made above. The formulated hypotheses with respect to farmers switching decisions are subdivided into three groups, i.e., factors associated with the competitors' actions, the local share of members and the spatial and temporal arrangement of features (spatial and temporal effects).

3.1. Competitors' actions

A major reason for our spatial approach rests upon the heterogeneity of switching options across space implying varying switching incentives for farmers in the supply base. Farmers are confronted with the price incentives relevant to their area of location. Producer prices are increasingly volatile (Barton, et al., 2011) and difficult to predict; they depend very much on international marketplaces and policies. Hence, from a farmer's perspective, current price differences may serve as a reasonable point of reference for the potential realization of economic returns. Farmers seeking to maximize their prospective income may therefore strongly react to current price differences regarding their actual switching decisions. Since prices and extant switching options vary over space, we hypothesize that:

H1: The higher the competitors' prices compared to the prices paid by the FC in a given area, the more farmers defect the FC in that area (main hypothesis)

The literature dealing with members' commitment towards their cooperatives often considers investor-owned firms or spot markets as the alternative options for farmers to sell their products (Fulton, 1999; James Jr. and Sykuta, 2006; Roe, Sporleder and Belleville, 2004). While originally, as one of the classic cooperative principles, cooperatives are not supposed to directly compete with each other, the structural change as well as legal transformations lead to situations, where cooperatives no longer comply with that principle (Zeuli and Bentancor, 2005).

Given the competition of processing cooperatives for raw materials, the simple view on farmers' alternative marketing options and their organizational peculiarities do not longer apply. In line with that, Zeuli and Bentancor (2005) used a survey among Wisconsin dairy farmers to approach farmers' switching behavior under cooperative and non-cooperative competition. From their findings, they conclude that cooperative members are less likely to switch if the firm that is trying to lure them away is an investor-owned firm and not a cooperative. Hence, the form of the competing organizational businesses may influence the switching decisions in the FC's supply base and we hypothesize that:

H2: Prices paid by competing cooperatives in an area are associated with more farmers defecting from the FC in that area than comparable prices paid by investor-owned competitors.

In the dairy sector, for instance, a farmer's switching decision is typically a consequence of a competitor making an offer to buy the farmer's milk (Zeuli and Bentancor, 2005). The switching decisions in the supply base are therefore inexorably linked to the efforts of competitors in luring the farmers to deliver to their companies. This in turn is directly associated with the competitors' growth strategies: increasing production, e.g., to achieve economies of scales can be accomplished by providing incentives to increase production in the existing supplier base or by gaining new farming suppliers. Since the former is difficult to implement (restricted resources on the farming level: staples, quotas etc.) and time consuming, the latter seems like a sensible strategy especially in the short run. We therefore hypothesize:

H3: The higher the relative increase in production volume of competitors operating in an area, the more FC farmers defect to competitors in that area.

Given that a processor needs to provide incentives to increase production, a substantial production quantity may imply that a processor meets its farming suppliers interests better than any outside option. Additionally, larger processors can be attributed to have lower costs per output due to economies of scale. Hence, large-scale processors theoretically should have a competitive advantage, which should generate resources that enable them to please their suppliers. We therefore hypothesize that:

H4: The higher the competitors' production/traded volume in a given area, the more FC farmers defect to competitors in that area.

3.2. Local share of members

In the following we discuss two potential rationales for the association of local share of the FC's members with member switching.

Regarding the local market for produce, other farmers delivering to a competitor in an area may serve as an indicator for the existence of actual switching options. Furthermore, in the dairy sector, there is a higher likelihood that the farmers in the supplier base are located relatively close to the competitors' milk collection route, which implies relatively lower additional expenses for the collection of those farmers' milk. Since the buyers have to bear the costs of milk collection (Graubner, Koller, Salhofer and Balmann, 2011), the farmers located close to the existent competitors' milk collection routes may attract the competitors' attention first in case of competition for product.

Next to market-related considerations, the local share of FC members can be assumed to have an influence on the level of social cohesion, also known as social capital, which can be assumed to reduce the importance of actual prices paid to farmers in favor of non-monetary benefits (Feng, Friis and Nilsson, 2016; Nilsson, Svendsen and Svendsen, 2012). The agricultural cooperative is a network organization by design, which underlines the importance of member-member relationships for the emergence of social capital (Hong and Sporleder, 2007). Since social networks are affected by spatial proximity (Butts, 2002; Liben-Nowell, et al., 2005) the local share of FC members may serve as an indicator for the degree of their social interaction, and thus for the social cohesion within the cooperative. For example, Hansen et al. (2002) as well as Feng et al. (2016) found that a dispersed membership is associated with lower levels of social capital.

Following the above rationales, we hypothesize that:

H5: The lower the share of FC members compared to farmers delivering to competitors in a given area, the more farmers defect from the FC to competitors in that area.

H6: The lower the share of FC members in relation to farmers delivering to competitors in a given area, the stronger is the reaction to price incentives accompanied by more farmers defecting from the FC to competitors in that area.

3.3. Spatial and temporal effects

According to the first law of geography, "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970: 236). Since social networks and interaction are influenced by space (Butts, 2002; Liben-Nowell, Novak, Kumar, Raghavan and Tomkins, 2005), and it is well-known that economic decision-makers are influenced by other decision-makers (Banerjee, 1992; Manski, 2000), one can assume a higher influence of decision-makers located close by, which emerges as a spatial impact.

This impact, which may happen directly through communication or indirectly through observation, provides a rationale for the influence of neighboring farmers (Foster and Rosenzweig, 1995). Assuming that individuals' switching decisions trigger switching decisions of farmers located close by, we hypothesize that:

H7: The switching decisions in one area of the FC's membership base spatially correlate to neighboring areas.

Theoretically, spatial interdependence can be assumed for other factors affecting FC members' switching decisions as well. However, hypotheses are not formulated due to identification issues.

Next to the potential autocorrelation across space, a limited number of supplying farmers per areal unit suggests temporal dependence of switching decisions. Hence, we hypothesize that:

H8: The more FC farmers switched during the last year, the fewer FC farmers switch during the subsequent year.

4. Material and methods

The formulated hypotheses are empirically tested by means of objective indicators potentially available to a cooperative. In the following sections, we describe the material and methods used for subsequently performed analysis.

4.1. Material

Data is drawn from three sources. First, a unique data set encompassing a total of 2004 switching decisions over seven years was provided by a large European dairy cooperative (FC in the following). The information on switching decisions, i.e., the notice of termination, is temporally (year) and geographically (county) referenced. Each farmer maximally switched once in the study period, and cases of farmers who completely quit production are excluded. Additionally, the yearly quantity of suppliers per county was provided, indicating the spatial distribution of the overall member base.

Second, the yearly occurrence of dairy producers per county was gathered from the official regional database. Data on the number of dairy farms per county were available for three years in the period in question (year 1, 3, and 7).

Third, the FC's and competitors' annual average market prices, processing quantities and organizational forms were gathered from an agricultural statistics provider.

Testing of the above hypotheses required additional data preparation at county level. Initially, we remove all counties that have no neighboring relation to any of the other counties, which allows for the calculation of weights matrices based on neighborhood relations (see chapter 4.2.). Then, we delete the counties that have no cooperative suppliers during the course of the observation period. This procedure enables the calculation of switching rates (share of switching farmers in the counties' total FC membership base) per county. The initial 65 counties in the data set reduce as a result to 60 counties observed over seven years. The calculation of switching rates enables comparison of switching risks across counties and years. However, risks implied by raw rates are likely biased by the counties' membership base (Anselin, 2006). Hence, we correct for variance instability by Empirical Bayes Rate

Smoothing (Bailey and Gatrell, 1995), resulting in Empirical Bayes Corrected Switching Rates.

The missing numbers of overall dairy farmers per county for the years 2, 4, 5, and 6 are imputed by linear interpolation. This procedure allows to calculate the rate of the concentration of the counties' FC's membership base (share of the counties' total FC's membership base in the counties overall dairy farmer population) for each year. This measure is corrected by Empirical Bayes Rate Smoothing as well, leading to Empirical Bayes Corrected Concentration of Membership Rates.

To include the competitors into the analysis, we select all other processors relevant for the counties under observation. During the observation period, several changes occurred in the sector. In case of takeovers and acquisitions and if the companies' locations remained, the observations (competitors) are merged. In total 96 competitors are considered in the analysis. However, due to unavailability of price information in respective years and terminations of business, the panel is unbalanced. Since there is only information on the state as well as the town of the companies' location, we look up the coordinates of all competitors' locations and thus generate a spatial point pattern.

To obtain the relevant competitors' prices per county, it has to be taken into account that a single county can overlap with the catchment areas of several competitors. To overcome this problem, an average of the prices of the relevant competitors was calculated for each county. Assuming average spatial extents of competitors' catchment areas allow calculating the average price differential of competitors' prices, production quantity and growth as well as the share of cooperative organizations competing for each county. Since there is only scarce knowledge on the spatial extent of catchment areas, we test several specifications. Among others, we used information on average catchment distances based on sector inquiries to calculate realistic average price incentives for the respective counties.

Table 2 gives an overview of the two obtained measures of rates and other determinants based on one chosen specification.

4.2. Methods

The absence of spatial randomness concerning the switching quotas requires the utilization of spatial econometric models, which allow for dependence between observations. This is due to the fact that the conventional assumption of independent observations is violated. So, the application of conventional regression models would imply ignoring the violation of independence, what would produce estimates that are biased and inconsistent (LeSage and Pace, 2010). Spatial analysis includes regularly two distinct types of information, i.e., the attributes of a spatial feature and its spatial location. Thereby, the spatial arrangement of spatial features needs to be formalized to allow for the explicit consideration of space.

In the literature, alternative approaches to incorporating spatial dependencies in a regression model exist (Zubek and Henning, 2016). Formally, these approaches differ regarding the inclusion of a spatial lag for the error term, a spatial lag for the dependent variable, or a spatial lag of the independent variables:

$$y = \alpha\iota_n + \rho Wy + X\beta + W_1X_1\theta + u \tag{1a}$$

$$u = \lambda Wu + \varepsilon \tag{1b}$$

$$\varepsilon \sim N(0, \sigma^2 I_n) \tag{1c}$$

In equation (1) y is the n x 1 vector of dependent variable observations; $\alpha_{\iota n}$ represents the region specific intercepts. X is the n x k explanatory variable matrix with β an associated n x 1 vector of coefficients. σ^2 is the scalar noise variance parameter; the n x n matrix W contains information regarding the spatial relationship between observations[1].

The spatial lag of the dependent variable (Wy) is a n x 1 vector containing a (weighted) average of the y-values from neighboring regions. The n x k matrix W_1X_1, which is the spatial lag of the explanatory variables, contains (weighted) averages of the explanatory variable values from neighboring regions (LeSage and Pace, 2010). X_1 is a subset of all explanatory variables X. W_1 can equal W, but also different specifications for W_1 are possible. Further, ρ is called the spatial autoregressive coefficient and λ the spatial autocorrelation coefficient, while θ like β is a k x 1 vector of unknown parameters (Elhorst, 2010). The spatial error model (SEM) results as a special case from equation (1) setting $\theta = 0$ and $\rho = 0$, i.e. the spatial dependencies are exhibited only by disturbances reflecting the spatially autocorrelated error term (Anselin and Bera, 1998). Assuming spatial dependencies are captured by a spatial lag of the dependent variable, i.e. $\theta = 0$ and $\lambda = 0$, results in the spatial autoregressive model (SAR), while the spatial mixed model (SMM) is an estimation that simultaneously allows the estimation of a spatial lag and a spatial error model (LeSage and Pace, 2010). Finally, spatial dependencies can be incorporated via spatial lags of the dependent ($\rho \neq 0$) and the independent ($\theta \neq 0$) variables. This approach refers to the spatial Durbin model (SDM).

Estimating the SDM as well as all other spatial regression models using panel data implies the additional opportunity to control for unobserved heterogeneity via specific spatial and time-period effects (Elhorst, 2010). A space-time model with spatial specific and time-period specific effects takes the form:

$$y = \alpha\iota_n + \rho Wy_{it} + X_{it}\beta + W_1X_{it}\theta + \mu_i + \xi_t + u_{it} \tag{2a}$$

$$u_{it} = \lambda Wu_{it} + \varepsilon_{it} \tag{2b}$$

$$\varepsilon_t \sim N(0, \sigma^2 I_n) \tag{2c}$$

ε_{it} is an independently distributed error term with zero mean and variance σ^2. In equation (2), we assume that W is constant over time, as well as that the panel is balanced.

In fact, spatial units likely differ in their background variables. These are usually space-specific time-invariant variables, which are difficult to measure or to obtain, but which

[1] The specification of the spatial weights is a frequently discussed problem, because unless the weights are based on a formal theoretical model for social or spatial interaction, their specification is often ad hoc. In practice, the choice is typically driven by geographic criteria indicated by contiguity or relative distance of geographic locations or entities. The simplest case of the weights matrix is a binary matrix, where the entries of the matrix are one when two spatial entities are neighbors and, zero when they are not. By convention, spatial weights matrices are usually row standardized Anselin, L., Le Gallo, J., Jayet, H. (2008). Spatial panel econometrics. *The econometrics of panel data*. Springer, 625-660.

influence the dependent variable. One approach to account for this heterogeneity is to introduce a variable intercept μ_i for each spatial unit i that represent the effect of the omitted variables that are peculiar to each spatial unit considered. Those spatial specific effects control for all time-invariant variables, whose omission would bias the estimates. Justification for time period-specific effects ξ_t is similar. They control for all spatial-invariant period specific variables, whose omission could potentially bias the estimates (Elhorst, 2014). In the fixed effects model, for each region and for each time period, a dummy variable is introduced. So we can deal with individual-, time-, as well as with both, i.e. individual and time fixed effects.

Given the different model specification, the question of an appropriate model selection arises. Beyond statistical fit, a better and hence theoretically founded understanding of empirically observed behaviour and outcomes is an important aim of econometric analyses. Therefore, some scholars suggest selecting a concrete spatial model specification a priori on theoretical grounds (Ward and Gleditsch, 2008). In this paper, we combine both strategies. First, based on our theoretical consideration, we select the SDM as a model specification. To be able to control for unobserved heterogeneity (Elhorst and Fréret, 2009), we undertake a panel estimation of our theoretically preferred SDM approach (excluding spatially autocorrelated errors terms) including spatial and time specific effects.

Based on the estimated model we first test the random effects against the fixed effects model using Hausman's specification test (Baltagi, 2005). This test can also be applied when the model is extended to include spatially lagged dependent or explanatory variables (Elhorst, 2010). Moreover, we apply separate Likelihood Ratio (LR) tests to test whether included spatial and time specific effects, respectively, are jointly statistically significant.

Since the panel SDM includes the corresponding panel SAR and the corresponding panel non-spatial model as special cases, standard LR test can be applied to test which model specification is most appropriate to describe the data (Elhorst, 2010). Since the computation of a goodness-of-fit measure in spatial panel models is controversially discussed in the literature (see e.g. Elhorst (2010); Anselin and Bera (1998)), we also include the Bayesian (BIC) and Akaike (AIC) information criterion derived for the different model specification.

Before we present our main estimation results, following remark has to be pointed out regarding the interpretation of the estimated parameters of the spatial models. If ρ in equations (1,2) is not equal to zero, the conventional least squares interpretation of the parameter vectors in the SAR, SMM, and SDM is not valid (LeSage, 2008; Pace and LeSage, 2006). Accordingly, LeSage and Pace (2010) define the own region response, $\delta Y_i / \delta X_{ir}$, as the direct effect, while the cross-partial derivatives, $\delta Y_j/\delta X_{ir}$, are defined as indirect effects or spillover responses for $i \neq j$ (LeSage and Pace, 2010). The latter effect just captures spillover effects. These two scalar summaries add up to a scalar summary measure of the total impact associated with changes in the r_{th} explanatory variable on the dependent variable.

As mentioned above different possibilities to define the spatial weights matrix W exist, i.e. distance/radius based, k-nearest neighbor, or contiguity based, i.e. related to boundaries of administrative units. In this study we construct different W-matrices. K-nearest neighbors with k varying from three to seven. Regarding a distance based specification we calculated the W-matrix for radii of 0-20km, 0-40km, 0-60km, 0-80 km, 0-100km, and 0-120km. Further we used a simple contiguity matrix indicating neighboring relations if the spatial units (counties) share a boundary (W1).

Because the administrative units do not correspond to the investigated areas we calculated mean values for the explanatory variables that correspond to spatial contiguity, too. We used k-nearest neighbors running from three to seven as well as a radii of 100, 110, 120, 130, 135, 140, and 150 km.

5. Results

General tests on spatial panel autocorrelation give us evidence that we have to control for spatial dependencies in the dependent variable: Moran MI = 0.264, p > Z (7.674) 0.000; Geary GC = 0.745, p >Z (5.183) 0.000.

The hypothesis that the SDM can be simplified to the SAR must be rejected (LR test: 163. 3 df, p = 0.000) as well as the hypothesis that the SDM can be simplified to the SEM (LR test: 153.84, 3 df, p = 0.000). The same applies for the SMM (LR test: 8.35, 3df, p=0.039). Thus, the SMM, the SEM, and the SAR must be rejected in favor of the SDM. To choose between the random and fixed effects estimators we applied a Hausman test. It shows that a SDM with fixed effects is better suited than a SDM with random effects (42.97, df 7, p>0.000). This holds true for spatial, temporal as well as for both spatial and time-period fixed effects. LR tests that investigate if the spatial fixed effects or the time-period fixed effects are jointly insignificant indicate that these hypotheses must be rejected (p=0.000). These results justify the extension of the model with spatial and time-period fixed effects.

Following Anselin, Gallo, and Jayet (2008) we used LM test to test for a spatially lagged dependent variable and a spatial error autocorrelation, respectively. We achieved results of 8.640 (df 1, p < 0.000) when testing for the spatial lag and 39.496 (df 1, p < 0.000) when testing for a spatial error provided we did not include the spatially lagged independent variable. The LM test that tests the hypothesis of no general spatial autocorrelation (SMM) can be rejected, too (39.553, df 2, p <0.000).

Secondly, we apply LR tests to distinguish between the SDM including spatial and time-period fixed effects and the corresponding nested SAR, SEM, and SMM, as well as between the SDM and the corresponding nested standard panel specification excluding spatial lags on statistical grounds. All tests indicate that the SDM is the best specification for our data.

In section 4.2 we mentioned that we construct different W-matrices as well as different mean values that compose the explanatory variables. Comparisons of the corresponding AIC and BIC values of different model specifications show the best model fit for a SDM using the values of three nearest neighbors (the three nearest competitors to a given county) for the mean value calculation of the explanatory variables and W1 as W-matrix (the results of the different model specifications are available from the authors upon request). In case of a SDM including time-lags of the dependent variable the AIC and BIC values suggest also mean value calculation for the three nearest neighbors combined with a W-Matrix that includes neighbors in a radius of 80km. Please note that only small differences occur for the different model specifications, i.e. robustness of the chosen final specification.

In section 2 different hypotheses are introduced. In table 1 the hypotheses are summarized and complemented by corresponding explanatory variables.

Table 1: Summary of hypotheses and explanatory variables

Hypothesis	**Explanatory variable** (Measurement)
H1: The higher the competitors' prices compared to the prices paid by the FC in a given area, the more farmers defect the FC in that area	*Area_price* *(Average price of all relevant competitors for a given area)*
H2: Prices paid by competing cooperatives in an area are associated with more farmers defecting from the FC in that area than comparable prices paid by investor-owned competitors.	*Area_coop-price* *(Share of relevant cooperative competitors for a given area times Area_price)*
H3: The higher the relative increase in production volume of competitors operating in an area, the more FC farmers defect to competitors in that area.	*Area_prod-increase* *(Production at t+1 minus Production at t of relevant competitors for a given area)*
H4: The higher the production/traded volume of farmers in a given area, the more FC farmers defect to competitors in that area.	*Area_trading-volume* *(Production of relevant competitors for a given area)*
H5: The lower the share of FC members compared to farmers delivering to competitors in a given area, the more farmers defect from the FC to competitors in that area.	*Coop-dens* *(Empirical Bayesian corrected share of counties' FC cooperative membership base in the counties overall dairy farmer population)*
H6: The lower the share of FC members in relation to farmers delivering to competitors in a given area, the stronger is the reaction to price incentives accompanied by more farmers defecting from the FC to competitors in that area.	*Area_priceXcoop-dens* *(Area_price times Coop-dens)*
H7: The switching decisions in one area of the FC's membership base spatially correlate to neighboring areas.	*rho: estimated parameter for the spatial lag of the dependent variable*
H8: The more FC farmers switched during the last year, the fewer FC farmers switch during the subsequent year.	*Lag_switch-rate: estimated parameter for the time lag of the dependent variable*

Summary statistics of the variables are listed in table 2. The explanatory variables shown here correspond to the model selection done before, i.e. the explanatory variables on the county level depend on the selection procedure for the relevant competitors per county.

Table 2: Summary statistics

Variable		**Mean**	**Std.Dev**	**Min**	**Max**
Switching rate	Overall	0.03	0.04	0.00	0.36
	Between		0.02	0.01	0.08
	Within		0.03	-0.04	0.31
Area_price	Overall	30.30	2.50	26.95	36.80
	Between		0.40	29.38	31.06
	Within		2.47	27.40	36.90
Area_coop-price	Overall	16.29	9.13	0.00	36.45
	Between		9.05	0.00	30.43
	Within		1.62	13.39	22.87
Area_prod-increase	Overall	5.22	15.68	-23.00	73.00
	Between		7.97	-3.57	24.90
	Within		13.53	-26.14	69.70
Coop-dens	Overall	0.39	0.30	0.01	0.97
	Between		0.29	0.01	0.93
	Within		0.05	-0.03	0.62
Area_priceXcoop-dens	Overall	11.86	9.00	0.27	32.79
	Between		8.86	0.34	28.05
	Within		1.91	-0.84	19.74
Area_trading-volume	Overall	108.44	101.74	12.50	470.50
	Between		96.45	16.36	328.43
	Within		34.37	-39.08	269.35

Counties: 60 (N); Years: 7 (T)
Overall Observations: 420 ($N \times T$)
Note: Relevant competitors per county relate to the 3 nearest neighbors (competitors).

In table 3 the corresponding estimation results are listed with model (M) A1 is a SDM with both, time and individual specific effects, using Area_coop-price as well as Area_priceXcoop-dens; MA2 is the corresponding SDM with both, time and individual specific effects including Coop-dens as well as the Area_price. The models MB1 and MB2 correspond to MA1 and MA2 but differ with regard to the included time lag for the dependent variable. Note that the focus of the analysis lies on the testing of the formulated hypotheses. Hence, a full model including constitutive and interaction terms would only allow interpreting the constitutive effects as conditional effects (Brambor, Clark and Golder, 2006) and therefore prohibit testing of the formulated hypothesis regarding these main predictors. We therefore estimate MA2 and MB2 without interaction terms. In MA2 and MB1 the constitutive effects are omitted, because *Coop-dens and Area_priceXcoop-dens as well as Area_coop-price and Area_coop-price* show substantial correlation (0.99 and 0.11; z-scores: 0.99 and -0.24). Nevertheless, since omitting constitutive terms may bias the parameters of interest (Brambor, Clark and Golder, 2006), we also provide the estimations of the full models (M0, M0_Lag) in the appendix (see table A1).

Table 3: Estimation results

		MA1	MA2	MB1	MB2
Main	*Lag_switch-rate_*			-0.084 (1.73)*	-0.099 (2.04)**
	*Area_prod-increase_*	-0.058 (-1.23)	-0.056 (-1.17)	-0.051 (-0.93)	-0.051 (-0.91)
	*Area_trading-volume_*	0.505 (3.08)***	0.479 (2.84)***	0.661 (3.53)***	0.664 (3.41)***
	*Area_priceXcoop-dens_*	0.609 (3.09)***		0.717 (3.33)***	
	*Area_coop-price_*	1.212 (1.55)		1.515 (1.94)*	
	Coop-dens		0.626 (3.07)***		0.742 (3.33)***
	*Area_price_*		0.018 (-0.39)		0.056 (-1.1)
Wx	*Area_prod-increase__*	0.261 (3.30)***	0.252 (3.15)***	0.336 (3.68)***	0.32 (3.48)***
	Area_coop-price__	5.04 (2.92)***		4.937 (2.85)***	
	Area_price__		0.145 (-1.64)		0.177 (1.87)*
Spatial	*Rho*	0.399 (8.00)***	0.409 (8.22)***	0.396 (7.26)***	0.406 (7.46)***
Variance	*sigma2_e*	0.48 (14.30)***	0.487 (14.29)***	0.545 (15.43)***	0.554 (15.42)***
Direct	*Area_prod-increase_*	-0.03 (-0.71)	-0.026 (-0.47)	-0.009 (-0.14)	-0.017 (-0.28)
	*Area_trading-volume_*	0.541 (2.86)***	0.504 (2.86)***	0.697 (3.34)***	0.737 (3.88)***
	*Area_priceXcoop-dens_*	0.649 (2.93)***		0.752 (3.48)***	
	*Area_coop-price_*	1.885 (2.25)**		2.301 (2.93)***	
	Coop-dens		0.654 (3.61)***		0.797 (3.04)***
	*Area_price_*		0.042 (-0.75)		0.084 (-1.42)
Indirect	*Area_prod-increase_*	0.394 (3.23)***	0.383 (2.89)***	0.516 (3.52)***	0.468 (2.88)***
	*Area_trading-volume_*	0.322 (2.58)***	0.316 (2.30)**	0.407 (2.51)**	0.446 (3.12)***
	*Area_priceXcoop-dens_*	0.381 (2.69)***		0.438 (2.71)***	
	*Area_coop-price_*	9.14 (3.27)***		8.67 (2.94)***	
	Coop-dens		0.405 (2.86)***		0.49 (2.37)**
	*Area_price_*		0.272 (1.91)*		0.347 (2.19)**
Total	*Area_prod-increase_*	0.364 (2.51)**	0.358 (2.14)**	0.506 (2.70)***	0.452 (2.23)**
	*Area_trading-volume_*	0.863 (2.85)***	0.82 (2.71)***	1.104 (3.12)***	1.183 (3.79)***
	*Area_priceXcoop-dens_*	1.031 (2.96)***		1.19 (3.30)***	
	*Area_coop-price_*	11.026 (3.37)***		10.971 (3.27)***	
	Coop-dens		1.058 (3.49)***		1.287 (2.83)***
	*Area_price_*		0.314 (1.78)*		0.431 (2.22)**
ll(model)		-450.3942	-453.9963	-381.448	-384.673
Df		8	8	9	9
AIC		916.7885	923.9926	780.8961	787.3461
BIC		949.1105	956.3146	815.871	822.321

Note: *; ** and *** denote 10, 5 and 1 per cent significance level, respectively.

Table 3 shows for all estimated models a positive significant result for the spatial lag parameter ρ. Thus, the switching rate varies not randomly between regions but clusters spatially, i.e. we find clusters of high as well as clusters of low switching rates. In other words, the switching rate of a single region depends on the switching rates of its neighboring regions. This strengthens our consideration that spatial dependencies have to be taken into account when analyzing switching decisions. Moreover, H7 cannot be rejected, i.e. the switching decisions in one area of the FC's membership base spatially correlate to neighboring areas.

The results of the different models show a clear correspondence in significance and direction of estimated coefficients between the different models. With regard to the estimated total effects we found for all explanatory variables significant results. The *Area_price* has a positive significant impact on the switching rate, i.e. the higher the competitors' prices compared to the prices paid by the FC in a given area, the more farmers defect the FC in that area. Interestingly, the positive significant total effect is mainly driven by the estimated indirect effect, i.e. a spillover effect from the neighboring regions. In other words, in case *Area_price* in neighboring areas increases, the switching rate in the own region is affected significantly positive whereas an increase of *Area_price* in the own region does not influence the switching rate in the own region significantly.

For *Area_coop-price* a positive significant total effect is identified. Both, the direct and indirect effect are positive significant as well. Thus, prices paid by competing cooperatives in an area are associated with more farmers defecting from the FC in that area than comparable prices paid by investor-owned competitors (H2). The estimated coefficients for the *Area-prod-increase* show significances for the indirect as well as for the total effects. Thus, H3 cannot be rejected but it has to be considered that spillovers form neighboring areas drive the positive significant total effect. A corresponding adjustment of H3 would be "the higher the relative increase in production volume of competitors operating in the neighboring areas of the area the members are located in, the more members defect to competitors in that area."

Regarding the cooperative member density (*coop-dens*) positive significant total as well as direct and indirect effects are found. Therefore, H5 has to be rejected. We found that the higher the share of FC members compared to farmers delivering to competitors in a given area, the more farmers defect from the FC to competitors in that area. The interaction term of the area price and the cooperation density (*Area_priceXcoop-dens*) shows overall positive significant results. Hence, H6 has to be rejected as well.

The trading volume in an area (*Area_trading-volume*) influences the switching rate positively. Positive significant results for the direct, indirect and total effects imply that H4 cannot be rejected. In the models MB1 and MB2 we include a time lag for the dependent variable. In line with our expectation negative significant coefficients are found. Thus, the higher the switching rate of the last year, the lower the switching rate in the following year.

6. Discussion

Overall the results underline the importance of the spatial perspective for the analysis of cooperative member switching decisions, which is among others indicated by the significant spatial interdependence of switching decisions as well as the various significant results for the local determinants of switching decisions. Regarding the model selection, a SDM seems not only statistically, but also intuitively reasonable, since next to the dependent variable, the actual determinants of switching decisions are likely spatially autocorrelated. Additionally, the calculation of predictors based on spatial distances inherently introduces spatial autocorrelation among the determinants at county level, which is taken up by the spatially lagged predictors in the SDM specification.

The simulation of different weights matrices and mean values takes into account the lack of knowledge on the relevance of spatial distances with regard to members' switching decisions and provides exploratory insights. In fact, the construction of weights matrices is a frequently discussed issue (Leenders, 2002; LeSage and Pace, 2014). Using weights based on geographic distance has the advantage of being exogenous (LeSage and Pace, 2014) and the results for the implementation of various weights matrices indicates an overall robustness of the model. The best relative fit indicated by the AIC and BIC suggests an average calculation for the three nearest neighbors (three nearest competitors) combined with a W-Matrix including direct neighboring counties or counties in a radius of 80 km. These comparably low numbers of neighboring competitors obtaining the best fit may imply that the actions of few competitors are relevant for the FC members switching decisions on a county level. This seems reasonable, since a farmer may more likely switch to another buyer close by implicating a higher relevance of these buyers' activities, which again underlines the relevance of spatial proximity.

However, the choice of a uniform selection strategy of relevant competitors across space (same number of competitors or radius) likely violates the existence of spatially heterogeneous catchment areas in size and shape across space, implying that knowledge on the actual catchment areas could lead to a more accurate calculation of determinants. This inaccuracy in measurement of price incentives per county may explain that the total effect of *Area_price* is mainly driven by the estimated indirect effect. Since the spatial lag of the predictor *Area_price* is an average of this variable of the neighboring counties (here, all direct neighboring counties or counties within a radius of 80 km), the spatial lag comprises price incentives of more competitors. Hence, it could be the case, that the average of the three nearest competitors per county underestimates the spatial spread of price incentives. The same rationale may hold for the variable *Area-prod-increase*. Nevertheless, the significant impacts of *Area_price* and *Area-prod-increase* on the dependent variable support a general effect of local prices and increase in competitors' production on cooperative members switching decisions.

The obtained significant positive effects for *coop_dens* and *Area_priceXcoop-dens* lead to the rejection of *H5* and *H6* and a revision of the hypotheses. A high density of cooperative members per county may thus not indicate limited switching options and a high degree of social cohesion. In case of low overall commitment towards the cooperative, the members could induce each other to switch or even defect the FC cooperative collectively (Viergutz and Schulze-Ehlers, 2016) explaining a positive association of cooperative density and switching rates. On the county level, such an interdependence of switching decisions is also indicated by the significant spatial lag of the dependent variable, which is usually interpreted as the outcome of interacting agents (Anselin, 2002). However, the underlying social processes remain unobserved and the pattern reflecting social interaction might be spurious.

7. Conclusion

The article fills an important gap in the extant literature, by analyzing cooperative members' switching decisions based on objective indicators. Results confirm the overall appropriateness of a spatial approach and the significance of local indicators, i.e., prices, competitors' organizational form, competitors' production quantity, competitors' growth in production and cooperative member density were found to influence local cooperative members' switching decisions. Additionally, spatial interdependence of switching decisions as well as unexpected signs of effects hint at a potential relevance of social interaction for switching decisions.

Future research should not only overcome the weaknesses of the analysis, i.e. inaccuracy of measurements and level of observation, but also examine the social processes underlying switching decisions. This seems to be crucial, given the structural change in the agricultural sector accompanied by larger cooperatives implying more heterogeneous and anonymous membership bases.

Appendix

A1: Estimation results full model specification

		M0	M0_Lag
Main	*Lag switch-rate*		-0.093
			(1.91)*
	Area_prod_increase	-0.047	-0.034
		(0.98)	(0.61)
	Area_trading_volume	0.433	0.599
		(2.55)**	(3.04)***
	Area_priceXcoopdens	-0.103	-0.363
		(0.07)	(0.24)
	Area_coop_price	1.744	1.832
		(1.62)	(1.65)*
	Coopdens	0.753	1.122
		(0.51)	(0.73)
	Area_price	-0.059	-0.025
		(0.76)	(0.28)
Wx	*Area_price*	0.289	0.330
		(2.25)**	(2.39)**
	Area_prod_increase	0.267	0.330
		(3.34)***	(3.58)***
	Area_priceXcoopdens	-3.917	-3.846
		(1.38)	(1.32)
	Coopdens	3.984	3.706
		(1.39)	(1.26)
Spatial	*rho*	0.394	0.394
		(7.74)***	(7.04)***
Variance	*sigma2_e*	0.482	0.546
		(14.30)***	(15.42)***
Direct	*Area_prod_increase*	-0.021	0.004
		(0.48)	(0.06)
	Area_trading_volume	0.467	0.632
		(2.36)**	(2.90)***
	Area_priceXcoopdens	-0.444	-0.754
		(0.25)	(0.48)
	Area_coop_price	1.819	2.149
		(1.70)*	(1.90)*
	Coopdens	1.175	1.586
		(0.65)	(1.01)
	Area_price	-0.022	-0.001
		(0.27)	(0.01)
Indirect	*Area_prod_increase*	0.373	0.471
		(3.00)***	(3.61)***
	Area_trading_volume	0.279	0.368
		(1.94)*	(2.39)**
	Area_priceXcoopdens	-6.079	-5.704
		(1.38)	(1.22)
	Area_coop_price	1.062	1.266
		(1.66)*	(1.73)*
	Coopdens	6.612	6.009
		(1.52)	(1.29)
	Area_price	0.411	0.468
		(1.99)**	(2.23)**
Total	*Area_prod_increase*	0.352	0.474
		(2.33)**	(2.88)***
	Area_trading_volume	0.747	1.000
		(2.24)**	(2.82)***
	Area_priceXcoopdens	-6.522	-6.458
		(1.15)	(1.17)
	Area_coop_price	2.881	3.415
		(1.71)*	(1.87)*
	Coopdens	7.787	7.596
		(1.37)	(1.39)
	Area_price	0.389	0.468

Note: *; ** and *** denote 10, 5 and 1 per cent significance level, respectively.

Literature

Ajzen, I. and Fishbein, M. (2005). The influence of attitudes on behavior. *The handbook of attitudes* 173: 221.

Anselin, L. (2006). How (not) to lie with spatial statistics. *American journal of preventive medicine* 30: 3-6.

Anselin, L. (2002). Under the hood issues in the specification and interpretation of spatial regression models. *Agricultural economics* 27: 247-267.

Anselin, L. and Bera, A. K. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. *Statistics Textbooks and Monographs* 155: 237-290.

Anselin, L., Le Gallo, J., Jayet, H. (2008). Spatial panel econometrics. *The econometrics of panel data*. Springer, 625-660.

Bailey, T. C. and Gatrell, A. C. (1995). *Interactive spatial data analysis*. Longman Scientific & Technical Essex.

Baltagi, B. H. (2005). *Econometric Analysis of Panel Data*. Wiley.

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics* 107: 797-817.

Barraud-Didier, V., Henninger, M.-C., El Akremi, A. (2012). The Relationship Between Members' Trust and Participation in the Governance of Cooperatives: The Role of Organizational Commitment. *International Food and Agribusiness Management Review* 15: 1-24.

Barton, D., Boland, M., Chaddad, F., Eversull, E. (2011). Current challenges in financing agricultural cooperatives. *Choices* 26.

Bhuyan, S. (2007). The "People" factor in cooperatives: An analysis of members' attitudes and behavior. *Canadian Journal of Agricultural Economics-Revue Canadienne D Agroeconomie* 55: 275-298.

Bijman, J., Iliopoulos, C., Poppe, K., Gijselinckx, C., Hagedorn, K., Hanisch, M., Hendrikse, G., Kühl, R., Ollila, P., Pyykkönen, P. (2012). Support for farmers' cooperatives: Final report: European Commission. Brussels.

Brambor, T., Clark, W. R., Golder, M. (2006). Understanding interaction models: Improving empirical analyses. *Political analysis* 14: 63-82.

Butts, C. T. (2002). Predictability of Large-Scale Spatially Embedded Networks. In R. Breiger, K. M. Carley, P. Pattison (eds), *Dynamic Social Network Modelling and Analysis: Workshop Summary and Papers*. Washington, DC, 313-323.

Cechin, A., Bijman, J., Pascucci, S., Omta, O. (2013). Decomposing the Member Relationship in Agricultural Cooperatives: Implications for Commitment. *Agribusiness* 29: 39-61.

Durham, C. A., Sexton, R. J., Song, J. H. (1996). Spatial competition, uniform pricing, and transportation efficiency in the California processing tomato industry. *American Journal of Agricultural Economics* 78: 115-125.

Dusek, T. (2004). Spatially aggregated data and variables in empirical analysis and model building for economics. *Cybergeo: European Journal of Geography*.

Elhorst, J. P. (2010). Spatial panel data models. In M. F. a. A. Getis (ed), *Handbook of Applied Spatial Analysis*. Springer, 377-407.

Elhorst, J. P. (2014). Spatial panel data models. *Spatial Econometrics*. Springer, 37-93.

Elhorst, J. P. and Fréret, S. (2009). Evidence of political yardstick competition in france using a two-regime spatial durbin model with fixed effects. *Journal of Regional Science* 49: 931-951.

Feng, L., Friis, A., Nilsson, J. (2016). Social capital among members in grain marketing cooperatives of different sizes. *Agribusiness* 32: 113-126.

Feng, L., Nilsson, J., Ollila, P., Karantininis, K. (2011). The human values behind farmers' loyalty to their cooperatives. *5th international conference on economics and management of networks, Limassol*. 1-3.

Foster, A. D. and Rosenzweig, M. R. (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of political Economy*: 1176-1209.

Fousekis, P. (2011). Spatial Price Competition Between Cooperatives Under Hotelling-Smithies Conjectures. *Agricultural Economics Review* 12: 5.

Fulton, M. (1999). Co-Operatives and Member Commitment.

Fulton, M. and Giannakas, K. (2001). Organizational commitment in a mixed oligopoly: Agricultural cooperatives and investor-owned firms. *American Journal of Agricultural Economics* 83: 1258-1265.

Graubner, M., Koller, I., Salhofer, K., Balmann, A. (2011). Cooperative versus non-cooperative spatial competition for milk. *European Review of Agricultural Economics* 38: 99-118.

Greenhut, M. L. (1981). Spatial Pricing in the United States, West Germany and Japan. *Economica* 48: 79-86.

Gyau, A., Spiller, A., Wocken, C. (2011). Price or relational behaviours? Supplier relationship management in the German dairy industry. *British Food Journal* 113: 838-852.

Hansen, M. H., Morrow Jr, J. L., Batista, J. C. (2002). The impact of trust on cooperative membership retention, performance, and satisfaction: an exploratory study. *The International Food and Agribusiness Management Review* 5: 41-59.

Hansmann, H. (1996). The ownership of enterprise. 1996. *Cambridge Mass*.

Hernandez-Espallardo, M., Arcas-Lario, N., Marcos-Matas, G. (2013). Farmers satisfaction and intention to continue membership in agricultural marketing co-operatives: neoclassical versus transaction cost considerations. *European Review of Agricultural Economics* 40: 239-260.

Hess, S., Lind, L. W., Liang, S. (2013). Farmers' perceived transaction costs in relation to slaughterhouses of different ownership structure. *Agribusiness* 29: 96-111.

Hong, G. and Sporleder, T. L. (2007). Social capital in agricultural cooperatives: Application and measurement.

James Jr., H. S. and Sykuta, M. E. (2006). Farmer trust in producer-and investor-owned firms: Evidence from Missouri corn and soybean producers. *Agribusiness* 22: 135-153.

Kitchin, R. and Thrift, N. (2009). *International Encyclopedia of Human Geography: A 12-Volume Set*. Elsevier.

Kyriakopoulos, K. (2000). *The Market Orientation of Cooperative Organizations: Learning Strategies and Structures for Integrating Cooperative Firm and Members*. Van Gorcum.

Lang, K. A. and Fulton, M. E. (2004). Member Commitment and the Market and Financial Performance of the Saskatchewan Wheat Pool. *Current Agriculture, Food & Resource Issues* 5: 238 - 252.

Leenders, R. T. A. J. (2002). Modeling social influence through network autocorrelation: constructing the weight matrix. *Social Networks* 24: 21-47.

Lehmann, K., Dannenberg, P., Kulke, E. (2013). The Unjust Chain? The Value Chain of Milk in Germany. In C. Tamásy and J. R. Diez (eds), *Regional resilience, economy and society: Globalising rural places*. Routledge, 53-75.

LeSage, J. and Pace, R. K. (2010). An Introduction to Spatial Econometrics. In M. M. F. a. A. Getis (ed), *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications*. Berlin: Springer, 355-376.

LeSage, J. P. (2008). An introduction to spatial econometrics. *Revue d'économie industrielle*: 19-44.

LeSage, J. P. and Pace, R. K. (2014). The biggest myth in spatial econometrics. *Econometrics* 2: 217-249.

LeVay, C. (1983). AGRICULTURAL CO-OPERATIVE THEORY: A REVIEW*. *Journal of Agricultural Economics* 34: 1-44.

Liben-Nowell, D., Novak, J., Kumar, R., Raghavan, P., Tomkins, A. (2005). Geographic routing in social networks. *Proceedings of the National Academy of Sciences of the United States of America* 102: 11623-11628.

Manski, C. F. (2000). Economic Analysis of Social Interactions. *Journal of Economic Perspectives* 14: 115-136.

Mazzarol, T., Soutar, G.N., Limnios, E.M. (2012). Member Loyalty in Co-operative Enterprises: A Preliminary Assessment.

Morfi, C., Ollila, P., Nilsson, J., Feng, L., Karantininis, K. (2015). Motivation Behind Members' Loyalty to Agricultural Cooperatives. In J. Windsperger, G. Cliquet, T. Ehrmann, G. Hendrikse (eds), *Interfirm Networks: Franchising, Cooperatives and Strategic Alliances*. Cham: Springer International Publishing, 173-190.

Nilsson, J., Svendsen, G. L., Svendsen, G. T. (2012). Are large and complex agricultural cooperatives losing their social capital? *Agribusiness* 28: 187-204.

Ollila, P., Nilsson, J., von Brömssen, C. (2011). Changing member loyalty in producer cooperatives.

Ortmann, G. F. and King, R. P. (2007). Agricultural cooperatives I: History, theory and problems. *Agrekon* 46: 18-46.

Osterberg, P. and Nilsson, J. (2009). Members' Perception of Their Participation in the Governance of Cooperatives: The Key to Trust and Commitment in Agricultural Cooperatives. *Agribusiness* 25: 181-197.

Pace, R. K. and LeSage, J. P. (2006). Interpreting Spatial Econometric Models. *Regional Science Association International North American Meetings*. Toronto, CA.

Pascucci, S., Gardebroek, C., Dries, L. (2011). Some like to join, others to deliver: an econometric analysis of farmers' relationships with agricultural co-operatives. *European Review of Agricultural Economics*: jbr027.

Plant, R. E. (2012). *Spatial data analysis in ecology and agriculture using R*. cRc Press.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology* 88: 879.

Roe, B., Sporleder, T. L., Belleville, B. (2004). Hog producer preferences for marketing contract attributes. *American Journal of Agricultural Economics* 86: 115-123.

Rogers, R. T. and Sexton, R. J. (1994). Assessing the importance of oligopsony power in agricultural markets. *American Journal of Agricultural Economics* 76: 1143-1150.

Schulze, B., Wocken, C., Spiller, A. (2006). Relationship quality in agri-food chains: Supplier management in the German pork and dairy sector. *Journal of Chain and Network Science* 6: 55-68.

Tennbakk, B. (2002). Cooperatives, regulation and competition in Norwegian agriculture. *Zaragoza (Spain)* 28: 31.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic geography* 46: 234-240.

Viergutz, T. and Schulze-Ehlers, B. (2016). The Spatiotemporal Interrelatedness of Farmers' Switching Decisions. *2016 Annual Meeting, July 31-August 2, 2016, Boston, Massachusetts*. Agricultural and Applied Economics Association.

Ward, M. D. and Gleditsch, K. S. (2008). *Spatial regression models*. Sage.

Zeuli, K. and Bentancor, A. (2005). The Effects of Cooperative Competition on Member Loyalty. *Annual meeting, November 8-9, no. 31823. NCERA-194 Research on Cooperatives*.

Zubek, N. and Henning, C. H. (2016). Local Government, Spatial Spillovers and the Absorption of EU Structural Funds. *Journal of Agricultural Economics*.