The Spatiotemporal Interrelatedness of Farmers' Switching Decisions

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Abstract

The supply base of food processors has become increasingly unstable in the past decades. To enable buyers to reduce unfavorable events of accumulated contract terminations in the future, the factors determining farmers' switching decisions need to be understood properly. However, the extant empirical literature suffers from a lack of information on actual switching behavior and objective indicators such as real price differences. Additionally, although reports about high numbers of farmers switching at the same time suggest that the switching decision of the individual farmer is crucially influenced by its spatial and temporal context, this has so far not been investigated.

This article analyzes the spatiotemporal patterns of farmers' actual switching behavior based on a unique dataset. Specifically, we seek to detect group-like switching decisions as indicated by clusters in space and time using the space-time permutation scan statistic. We further try to explain accumulated switching by objective indicators. The analyses reveal two groups of spatiotemporally clustered switching decisions. First, there are clusters where many farmers switch on a particular day. Second, there are clusters covering longer periods in time with farmers switching herd-like in a specific area. A comparison of famers within and outside clusters with respect to relative prices suggests a modest relation, indicating a moderate relationship between price incentives and switching decisions. Additionally, we find statistical evidence that herd-like switching includes larger farms compared to farmers switching in other points in time.

Keywords: supply base dynamics, spatiotemporal clustering, space-time permutation scan statistic, group-like behavior, cooperatives

Introduction

Much has been written about the deterioration of relationships between cooperatives and their members in recent years (Burt and Wirth 1990; Fulton and Giannakas 2001; Hogeland 2006; Nilsson, Kihlen, and Norell 2009). According to the literature, major reasons for this observation include competence-based management problems and general disadvantages of the legal form (Cook 1995; Hansmann 1988; Nilsson 2001) resulting in lower economic performance, but also alienation of members and representatives due to growth and associated increased member heterogeneity (Fulton and Giannakas 2001; Nilsson, Svendsen, and Svendsen 2012). These problems lead to increased member fluctuations inducing costs of suboptimal capacity utilization and a costly acquisition of new suppliers. At the extreme, a crumbling supplier base could precede the buyer's demise, if increasing numbers of defecting suppliers develop an own dynamic and result in a vicious circle (Nilsson, Svendsen, and Svendsen 2012). Accumulated switching decisions are thus for buyers of crucial importance.

At the farmer level, the switching decision indicates the existence of a farmer expecting to get preferable conditions from another buyer. Such expectations are formed through own experiences on the one hand, but also through information acquired from other farmers, i.e., a farmer's social and professional network. This information can include simply the observation of others' switching, or more detailed information about underlying reasons. Assuming contagious effects as in case of innovation adoption (Rogers 1995), increased numbers of defecting suppliers might indicate the beginning of a vicious circle (Hirschman 1970; Nilsson, Svendsen, and Svendsen 2012) and should be cautiously monitored.[1] However, despite its empirical and theoretical relevance, an investigation of the interrelatedness of farmers' actual switching decisions is lacking in extant research.

The article seeks to fill this gap from a processor's supply base perspective using a unique dataset of actual switching behavior. We assume that farmers' switching decisions are spatially and temporally interrelated, and that this interrelation can provide meaningful information for buyers of agricultural raw materials who are interested in a stable supply base. Specifically, we are interested in whether and how farmers' switching decisions accumulate across space and time, and how that relates to objective and easily available indicators such as price relations or farm size. To approach the research gap, we seek to identify characteristic patterns of switching behavior by means of the space-time permutation scan statistic (Kulldorff et al. 2005). Insights obtained from the observation of the interrelatedness of farmers' switching decisions should help to get a better understanding of the underlying dynamic processes and generate new testable hypotheses which may contribute to the literature on farmers' switching behavior.

[1] Additionally, negative reputation effects on acquisition cost for new suppliers can be expected, if current non-members are deterred by information about high numbers of farmers switching to other firms.

The remainder of the article is organized as follows. First, we elaborate how the article complements the extant literature on farmers switching decisions and give a rationale for a systemic and spatiotemporal approach. Subsequently, hypotheses for the spatiotemporal characteristics of switching decisions are formulated based on several theoretical rationales. The article proceeds with the description of material and methods. Results of the analysis are presented and discussed, leading to a brief conclusion and outlook to future research.

Empirical studies on farmers' switching decisions

Even though there is a huge body of literature dealing with business relationships, there is little empirical work on (farmers') actual switching decisions. A review of the scarce literature mentioning farmers' buyer switching decisions revealed that most of the articles appear in the context of agricultural cooperatives, underlining the particular relevance of the issue for this organizational form. Most of the studies gather data by means of surveys and use various kinds of operationalizations of switching decisions, which can be roughly divided into two different categories. The first includes potential switching decisions as cooperative members' readiness or intention to abandon the buyer (Bhuyan 2007; Hernandez-Espallardo, Arcas-Lario, and Marcos-Matas 2013; Schulze, Wocken, and Spiller 2006). The second category deals with the farmers' stated past switching decisions or choices of business partners (Feng et al. 2011; Jensen 1990; Morfi et al. 2015; Morfi et al. 2014; Zeuli and Bentancor 2005). The objectives of these articles range from the analysis of human values (Feng et al. 2011) or motivational factors (Morfi et al. 2015) behind farmers' loyalty to their cooperative over the question, how attitudes and beliefs shape farming members' behavior, inter alia their intention to leave the cooperative (Bhuyan 2007), to factors associated with the choice of cooperative versus proprietary milk handlers (Jensen 1990). Populations sampled for the analyses are not less diverse. Examples include members of fruit and vegetables cooperatives in Spain (Hernandez-Espallardo, Arcas-Lario, and Marcos-Matas 2013), or in the Mid-Atlantic United States (Zeuli and Bentancor 2005) or a representative survey of Tennessee dairy farmers (Jensen 1990). Major determinants of switching intentions, or loyalty, as the positive pendant, include satisfaction with collaboration (Schulze, Wocken, and Spiller 2006), information or prices (Feng et al. 2011; Hernandez-Espallardo, Arcas-Lario, and Marcos-Matas 2013; Morfi et al. 2015; Zeuli and Bentancor 2005), as well as participation in the cooperative (Bhuyan 2007). Hansen et al. (2002) furthermore provide evidence for the relevance of group cohesion in cooperatives.

The variation in above studies' goals and measurement strategies leaves us with insights which may be difficult to generalize. Additionally, the current knowledge on farmers' switching behavior reveals three important gaps, which we try to overcome with the present study. First, there usually is a lack of information on actual switching behavior. The captured stated (non-)switching intentions or stated past actions may be appropriate for the intended research questions, but they are also prone to well-known problems related to the attitude-behavior gap as well as recall bias. Second, the studies mainly refer to price satisfaction or general satisfaction with the performance of the business relationship rather than real prices and/or price differences which might trigger switching decisions. Third, despite reports about high numbers of farmers switching at the same time (Dermody 2015) and bank-run like events reported in the literature (Nilsson, Svendsen, and Svendsen 2012), which suggests interdependence of switching decisions among farmers, an investigation of this phenomenon is lacking in extant research. The mainly cross-sectional studies cannot test for system dynamics.

Defining switching decisions in space and time

A switching decision means that a farmer chooses to trade with another buyer at a more or less distant future point in time. Thus, we are dealing with decision-makers under uncertainty who are subject to incentives created by the respective environment. In this section, we argue that incentives to switch can be expected to vary over time and space.

In line with the bounded rationality assumption (Simon 1959), individuals can further be assumed to form heterogeneous expectations based on prior experiences and additional information gathered from peers or the like, leading to heterogeneous responses to objectively equal incentives. This has been shown, e.g., by Lines and Westerhoff (2010) for inflation expectations or by Baak (1999) for price expectations on cattle markets. In the following, we will discuss how space can be understood as a proxy for the decision context, i.e. incentives, as well as for the information flow and thus expectation formation in networks. We explicitly set aside softer factors such as values or norms which have been shown earlier to affect switching intentions. This is not to say that these factors are not important. Our decision is rather driven by the desire to develop a model which relies on objectively observable variables.

Space as a determinant of the decision context

We assume that the spatial location and the time a decision takes place in, i.e., the spatiotemporal context, captures many of the objective factors affecting the farmer as a decision-maker. Switching options and actual prices paid to farmers vary over space, leading to differences in relative buyer attractiveness (Falkowski 2015). Additionally, spatial heterogeneity can be assumed for other relevant factors, such as the farmers' input factor markets (namely, land), farm characteristics as well as further factors influencing production. Since most of these factors vary over time as well, the individual farmer has to deal with a constantly changing environment and information base for the switching problem. We argue that the complexity in distribution of factors affecting each farmer can be reduced by means of the first law of geography, i.e., "everything is related to everything else, but near things are more related than distant things" (Tobler 1970, page 236). This rather vague law with respect to space can be extended to include both space and time (Miller 2004). Hence, neighboring farmers may likely face similar switching incentives from their objective environment at a similar point in time. Extending this to actual switching decisions, a farmer's switching decision should imply an increase in probability of a neighboring farmer's switching decision due to the similarity of the objective environment.

Space as a determinant of social networks

Besides the rationale for a spatiotemporal determinant of switching decisions, an economic decision-maker is influenced by other decision-makers (Manski 2000; Banerjee 1992). Theoretically, the model of the individual farmer reacting to his environment can thus be extended to an individual embedded into social networks (Granovetter 1985). The social networks in turn are determined by spatial proximity (Butts 2002; Liben-Nowell et al. 2005). Hence, we can assume a spatial impact through social networks on a decision-maker, what provides a rationale for the impact of a neighborhood (Ellison and Fudenberg 1993) or neighboring farmers (Foster and Rosenzweig 1995) on farmers (switching) decisions. This impact may happen directly through communication or indirectly through observation.

Dynamics in the farming supplier base

Acknowledging the above described processes, the decision-making takes not only place in particular spatiotemporal contexts, but also "generates spaces and times with variable reaches and intensities" (McCormack and Schwanen 2011, page 2802). Taking into account this endogeneity, we are confronted with a spatial-dynamic process that links economic actors over space and time (Wilen 2007) and makes the prediction and control of switching decision a difficult task. However, spatiotemporal processes are supposed to generate patterns that potentially are predictable (Wilen 2007). Many firms spend a lot of effort and time to predict and control their supply system, but struggle with its dynamics and complexity (Choi, Dooley, and Rungtusanatham 2001). Complex systems that consist of networks of interacting actors have a dynamic and aggregate behavior evolving from the individual activities. This aggregate behavior, which is sometimes termed as emergence (Harper and Lewis 2012), can be described without detailed knowledge of the behavior of the individual (Holland and Miller 1991). Examples for such events of emergence in the context of economic interaction are knowledge spillovers or herding behavior (Harper and Lewis 2012). Since the individual farmer faces a continuously changing environment and reaches the point, where the farmer decides to switch to another buyer, the switching decision implies that a farmer, who is spatiotemporally close to the switching farmer, may probably face similar contextual incentives to switch the buyer. The similarity of incentives increases the likelihood that the nearly located farmer may switch as well. Furthermore, the switching behavior could also drive other farmers to switch via social interconnection. Thereby, the distance in space and time reflects a general likelihood of relation and interaction in the network, what may cause in combination with the contextual factors the emergence of spatiotemporal patterns. Knowledge about the existence of emergence at the micro-macro link in relation to switching decisions, may help to better understand the processes leading to switching decisions as well as to prevent switching activities in the supply base. To facilitate this, knowledge about the dynamics and typical patterns in the farming supply bases is needed. Therefore, the article sheds light on farmers' switching decisions from a supply base perspective. This innovative approach may leverage the early identification of loyalty related problems in the supply base of agricultural processors.

Hypotheses

Considering the complexity and dynamics that decision-makers face, we aim at an analysis of the resulting patterns of actual behavior in space and time. We specifically try to identify typical patterns of switching decisions. The patterns in the supply base can deliver hints of the underlying data generating processes. Additionally, we seek to evaluate the extent of group-like switching decisions and how decisions are interrelated across space and time. We further aim at deriving insights about the relation between such phenomena and two objective indicators lacking in extant research.

Given the elaborations in the previous sections, we can formulate the following hypotheses. First, since farmers near in space and time face similar contextual factors and have tendencies to affect each other, one can expect, that switching decisions are highly interrelated across space and time. That will result in spatiotemporally clustered switching behavior, which can be described and analyzed. Therefore, we hypothesize that:

H1: There are spatiotemporal clusters, i.e., whole groups of switching farmers in relative spatial closeness and in a relatively short period, in the spatiotemporal distribution of actual switching decisions.

Second, it might be reasonable to assume that the farm size, measured as the traded volume of the switching farmer, plays a role in its effect on the system and therefore the emergence. Thereby, the effects of volume can be twofold. A large loss of supply in a region may imply reactions by the buyer, e.g., a change in service or operating area. Such expectations may then affect closely located farmers in their prospects for their business relationship and induce them to switch as well. In addition, a large traded volume may imply a large farm size or specialization in the respective area, what could imply that those farmers serve as local role models. Hence, provided that the existence of spatiotemporal clusters can be shown, we hypothesize that:

H2: The spatiotemporal clusters consist of relatively larger farms compared to those of farmers switching outside the spatiotemporal cluster.

Third, it is well known that price plays a crucial role in a farmer's choice of a buyer as well as it is an important determinant of loyalty and satisfaction with the extant business partner. In this context, we hypothesize that:

H3: Areas with relatively unfavorable relative prices do more often experience group-like switching events than areas with less unfavorable prices paid by the buyer.

Empirical strategy and material

We test our hypotheses by means of a unique dataset with actual switching decisions, covering a period of four years. The switching decisions are geographically referenced and temporally tagged, leading to a dynamic point pattern which allows the use of spatiotemporal tools and statistics. There are two major classes for the analysis of spatial point patterns (Haggett, Cliff, and Frey 1977; Upton and Fingleton 1985). One class uses test statistics based on measures of distances derived from the information on spacing of points to characterize the pattern. The other one is area-based and analyzes the variability of points in certain subsets of the space under investigation. Since we are interested in the actual spatiotemporal locations and compositions of clusters, but have no prior knowledge on the relevance of metric distances, the size or the composition of accumulative switching decision, we need a method that is highly flexible, systematically exploratory and reports the spatiotemporal locations of detected clusters. The retrospective space-time permutation scan statistic (STPSS) developed by Kulldorff et al. (2005) belongs to the area-based methods and can be assumed to fulfill these requirements. The scan statistic makes minimal assumptions about the time, the geographic location or size of the clustering of events. Furthermore, the scan statistic does not need population at risk data. In our case, using only the switching decisions is appropriate, because the spatial distribution of farmer suppliers may not reflect the actual population at risk due to geographical variation in switching opportunities caused by, e.g., imperfect spatial markets.

The STPSS allows detecting significant spatiotemporal clusters in the pattern of switching decisions. These clusters are also known as hotspots of space-time interaction within patterns of spatiotemporal points or events. The detection of such clusters are important in various contexts such as criminology or epidemiology, because they may indicate certain data generating processes or point at emergent trends (Tango 2010). In line with the objectives, we seek to identify such clusters in order to describe them and relate them to farmers' characteristics as well as external factors affecting the switching decision.

Space-Time Permutation Scan Statistic

In the following we introduce the functionality of the STPSS developed by Kulldorf et al. (2005). The STPSS belongs to a broader family of spatial and space-time scan statistics. In general, a scan statistic is used to detect clusters in a point process (Kulldorff 1997). First described by Naus (1965) in a one-dimensional setting, scan statistics have been studied and extended by several researchers. Temporal (Wallenstein 1980; Weinstock 1981), spatial (Kulldorff 1997) and spatiotemporal (Kulldorff 2001) scan statistics were developed and widely applied in various disciplines, namely epidemiology, ecology, criminology etc.. In essence, scan statistics use a scanning window that moves across the dimensions of interest. In the spatial setting there is a mostly circular window imposed on a map with the centroid moving across the study region. For any location of the centroid, the radius of the window is changed continuously and takes any value between zero and some upper limit (Kulldorff 1999). In the spatiotemporal setting, the window is modified such that instead of varying circles across space, varying cylinders are used. Whereas the base of the cylinder represents the space, the height of the cylinder represents the time (Kulldorff 2001). For each location and size of the window, the number of the observed points (or cases) are counted and compared to the expected number (see below). Due to the varying nature of the shifting scanning window, the scan statistic searches for clusters without making any a priori assumptions about the location, the size and/or the timespan. However, the large quantity of potential clusters implies a multiple testing problem. Thus, the statistical significance of the cluster under consideration is evaluated taking into account this problem (Kulldorff et al. 2005). The STPSS is a valuable extension of space-time statistics since it does not need any population at risk data. This implies a special probability model, which we elaborate in the following based on the article by Kulldorff et al. (2005).

Initially, the study area and time period of interest is subdivided into areas (z) and time periods (d) to assign and aggregate the points or cases. The areas are obtained by imposing a spatial grid on the map. In the software package SaTScan™ v9.4.2. (Kulldorff and Information Management Services 2015), if no grid-file is specified, each observation (or switching decision) serves as a grid point. The time periods are usually indicated by the smallest temporal unit available. c_{zd} represents the observed number of cases in area z at time d. The total number of observed cases in the overall study area and period (C) can then be calculated as:

(1) $$C = \sum_z \sum_d c_{zd}$$

Then, conditioning on the observed marginal, the expected number of switching decisions μ_{zd} is calculated for each area z and time-slot d:

(2) $$\mu_{zd} = \frac{1}{C} (\sum_z c_{zd})(\sum_d c_{zd})$$

In our case, the formula corresponds to the proportion of all switching decisions that occurred in area z times the total number of switching decisions that occurred during time slot d. The expected number of switching decisions in a particular cylinder A is the sum of all μ_{zd} belonging to that cylinder:

(3)
$$\mu_A = \sum_{(z,d)\in A} \mu_{zd}$$

It is thus assumed that the function generating the switching decisions operates uniformly across all time periods and areal subdivisions (Kulldorff et al. 2005). c_A indicates the observed switching decisions in a cylinder under consideration. Evidence that this cylinder contains a cluster is given by the Poisson generalized likelihood ratio (GLR):

(4)
$$\left(\frac{c_A}{\mu_A}\right)^{c_A} \left(\frac{C - c_A}{C - \mu_A}\right)^{(C- c_A)}$$

Across all cylinder radii, heights and starting locations, the one with the highest GLR constitutes the one least likely to have occurred by chance. Therefore, it is the primary candidate for a true space-time cluster. Possible secondary clusters are calculated by the STPSS as well. By means of Monte Carlo hypothesis testing, pseudo significance values are established for the identified clusters (Kulldorff et al. 2005).

Material

The dataset used for this analysis encompasses a total of 1,236 switching members of a large European processing cooperative over four years. The individual switching decisions are temporally (day of receipt of termination) and geographically (municipality) referenced and complemented by the individual cancellation dates as well as the farmer’s production/traded volume. Each farmer only switched once in the study period, and cases of farmers who completely quit production are excluded from the sample. Typical for cooperatives, the notice has to be handed in per the end of a calendar year to end the business relationship two years later. The exact dates of notice during the course of the years therefore enable us to analyze temporally dispersed decisions that lead to the same outcome in terms of effective termination. Furthermore, competitors’ and the cooperative’s annual average market prices were gathered from an agricultural statistics provider. For reasons of confidentiality, we cannot provide more detailed information at this point. We masked the data when necessary, descriptions are based on aggregates and we do not provide background information relating the sector to secure data privacy.

Analysis and results

The more than 1000 switching decisions span over four years, with the fourth year containing over 50 per cent of all cases in the study period. The distribution of switching decisions during the course of the years is characterized by relatively low amounts of switching decisions in the first half of the year. In the second half of the year, the switching decisions gradually increase with a maximum of switching decisions in December for each year. No cases are recorded at the weekend. Furthermore, there is no particular day capturing most of the switching decision in the course of a week.

Since the spatial reference refers to the municipality of the switching farmer, a random point inside the municipality was assigned for each switching decision. This procedure creates a point pattern, which consists of a unique spatial location for each case. The smallest convex set containing these generated points has an area almost corresponding to the size of the US-State of South Carolina. In that context, it has to be mentioned that the random assignment of switching decisions introduces inaccuracy on the level of the municipality. However, with a total amount of 2,195 municipalities in the convex set and a total of 338 different municipalities being subject to a switching decision, most of the information residing in the relative positioning of switching decisions in the point pattern remains. Furthermore, the STPSS is known to be robust regarding such common data deficiencies (Malizia 2013).

A dynamic visualization of switching decisions reveals wavelike patterns that become more frequent during the course of each year, but also random noise as well as whole groups of points appearing in a region on the same day. In order to find and analyze statistically significant local clusters of switching decisions in the spatiotemporal distribution, we employ the STPSS for every year. Since all switching farmers in a particular year end up having the same date of actual termination of the business relationship, thus, having the same outcome with regard to the defected cooperative, it seems reasonable to analyze each year separately. In addition, the switching decisions in each year imply a change in the underlying population at risk, i.e., the supplier base of the cooperative that may switch, which would bias the results of the STPSS if it was executed for all years together.

Implementation through SaTScan™

The following are the parameter values that we used in our runs for each year respectively. In order to utilize the full information in the dataset, a retrospective analysis was used. The STPSS scanned for areas with high rates of switching decision with days as timely units. Even though there are other spatial windows available, we used a circular window shape, because it is reported to obtain good results for a lot of different processes under consideration, while requiring less computational resources than, e.g., elliptic shapes (Kulldorff et al. 2006). A maximum spatial cluster size of 50 percent of the population at risk and a maximum temporal cluster size of 50 percent of the study period, in this case 6 months, were defined. The settings assure to obtain local clusters, which can be analyzed as a subset of the yearly point pattern. The reported secondary clusters are enforced not to overlap in order to obtain the clusters characterized by the highest significance values. The number of replications is kept to the default set to 999.

Table 1 contains the characteristics of the detected clusters by year, ranked by pseudo significance values. Six out of ten clusters refer to the fourth year under investigation, corresponding to this year's high share in overall switching decisions. The radiuses of the obtained clusters range from 11.01 to 58.71 km. The clusters consist of five to 102 switching decisions. Five out of ten clusters cover only one single day. The maximum temporal length is more than four months.

Table 1: Summary of the detected spatiotemporal clusters

Cluster	Year	Radius (km)	Start Date	End date	P-Value	c_A	μ_A
1	1	11.01	6th January	6th January	0.007	5	0.26
2	2	27.91	3rd November	3rd November	< 0.001	16	1.41
3	3	20.12	2nd January	2Nd January	< 0.001	27	4.46
4	3	30.29	2nd May	21st July	0.018	11	2.16
5	4	58.71	16th August	4th October	< 0.001	102	36.47
6	4	14.05	24tDecember	24th December	< 0.001	9	0.30
7	4	21.35	6th February	27th June	< 0.001	29	6.69
8	4	12.38	10th July	1st August	< 0.001	9	0.52
9	4	32.47	24th October	12th December	< 0.001	45	16.95
10	4	34.12	8th October	8th October	0.046	8	0.74

c_A: Observed number of switching decisions inside the cluster
μ_A: Expected number of switching decisions inside the cluster
Source: Own calculations

The clusters which are limited to a single day lack an inner temporal component, because days are the smallest temporal units. However, the clusters spanning a time frame can be further analyzed regarding their spatiotemporal pattern. Here, the Mantel test (Mantel 1967), which tests for overall space-time interaction was used. In one (cluster 5) out of five clusters, the null hypothesis of spatiotemporal randomness could be rejected, indicating a statistical significant association of space and time in the appearance of switching decisions inside the clusters.

Production quantity

When comparing the farmers' characteristics inside a cluster to the farmers' characteristics outside a cluster, the problem of spatial heterogeneity arises. In this case, it can be inter alia assumed that there are typical regional farm sizes, meaning that a comparison of farmers' characteristics across different regions implies an inherent bias. Consequently, we compare the average production volume of farmers inside a cluster to the production volume of other farmers switching in the same area and year, which reduces the bias of spatial heterogeneity. However, this approach significantly lowers the subpopulation that can be compared to a given cluster, implying that not all clusters (clusters 1, 2, 3, 4 and 6) can be evaluated in comparison to their non-cluster counterparts.

The comparison was done using the Wilcoxon Rank Sum Test. Results indicate for cluster 7 and 8 that the farmers' production quantities inside the cluster were significantly higher than the production volume of farmers outside the cluster. Cluster 5 gave the opportunity to compare the upper quartiles of the cluster and non-cluster population due to the relatively large number of switching farmers. The Wilcoxon Rank Sum Test indicated a significantly larger production quantity of the cluster's upper quartile of farmers' production volumes compared to their non-cluster counterparts.

Implementation of price proxies

To include the influence of prices on accumulated switching decisions in the analysis, a local price proxy, which represents the relative financial superiority of switching at the respective time, is required. To calculate such a proxy for any given farmer, the buyer's competitors are localized and added to the cartographic material. Then, assuming uniform pricing, we draw a realistic average catchment area around each location based on reliable expert information. To reduce complexity, the area under research is subdivided into 60 spatial entities based on the administrative divisions of the country. For each of these, the spatially relevant competitors are identified. We calculate an average of the competitors' prices for each spatial entity and year. Then, we subtract the price paid by the cooperative per entity and year from the average competitors' prices. This procedure provides a price proxy, which represents the yearly average spatial entity specific incentive to switch indicated by relative prices. The higher the price proxy in an entity, the higher is the incentive for a farmer located in that spatial entity to switch to another buyer. Table 2 gives an overview of the distribution of price proxies in monetary units across the 60 entities for each year, as well as the overall quantity of switching decisions and clusters detected.

Table 2: Relative price proxy, switching decisions and clusters detected per year across all spatial entities

	Year 1	**Year 2**	**Year 3**	**Year 4**
Mean price proxy	0.798	0.446	0.619	2.257
Median price proxy	0.769	0.490	0.627	2.241
Std. dev. price proxy	0.194	0.209	0.214	0.434
Switching decisions	189	182	224	641
Clusters detected	1	1	2	6

Source: Own calculations

Table 2 shows that in year four characterized by higher relative prices and a higher standard deviation across the 60 entities, more farmers do switch and more clusters can be detected. The second year, to the contrary, is characterized by a lower mean price proxy, indicating a relatively low average price differential to the competitors associated with 182 farmers switching and a single cluster being detected.

In addition, the areas spanned by the spatiotemporal clusters can be related to the entities capturing the relative pricing information per year. To this end, the spatial entities falling into the area of the clusters are detected by targeting the overlap between the two geographies for each year. This procedure delivers a variable indicating for each year and entity, whether it is subject to a cluster. Subsequently, all 60 entities are ranked for each year ranging from the entity with the most advantageous competitors' prices (rank 1) to the entity with the least advantageous competitors' prices (rank 60). The previously constructed variable for the entities allows then to explore the ranks of the entities intersecting with the clusters on the ranking of the 60 entities. Table 3 presents the number of entities falling into the area spanned by the clusters, the range of ranks of those entities and their mean score on the ranking by price proxies of the 60 entities. We assume that the lower the rank, the stronger the price incentive in that area and year is compared to other areas.

Table 3: Quantity of spatial entities affected by spatiotemporal clusters per year and the respective ranks

	Cluster year 1	Cluster year 2	Cluster year 3	Cluster year 4
Number of entities overlapping clusters	1	1	3	18
Range of ranks	-	-	44 – 50	1 – 39
Mean (or rank)	44	50	48	16

Source: own calculation

In the years one to three, only few entities overlap with a detected cluster and range with a mean from 44 to 50 remarkably low considering 60 entities under consideration. In contrast, year four is characterized by almost one third of all entities being overlapped by a spatiotemporal cluster. Therefore, the low mean and range of ranks of these entities indicate that most clusters appear in areas characterized by relatively advantageous competitors' prices.

Discussion

The application of the STPSS for each year revealed clusters that are relatively narrow in space and time. Hence, hypothesis 1 is supported in that there are clusters in the spatiotemporal distribution of switching decisions in the course of each year. The detected clusters can be classified into two different types. First, there are spatiotemporal clusters where a group of farmers located nearby switch on a particular day (clusters 1, 2, 3, 6 and 10). Second, there are clusters which last for more than one day and farmers are switching gradually within a more or less big area. Of these clusters, the patterning of the largest cluster both in terms of number of switching decisions as well as in spatial extent (cluster 5) is in itself characterized by significant space-time interaction. For the other clusters, the Mantel test failed to reject the null hypothesis of spatiotemporal randomness, which could be a result of the relatively low sample sizes (Scheiner and Gurevitch 2001). There are two obvious processes that could have led to the existence of the two classes. The clusters or group-like switching decisions taking place on a particular day can be the outcome of a collective decision among the respective farmers in that region. The other class of clusters could be the outcome of farmers observing the switching decisions of other farmers in that region, driving them to switch as well due to a change in expectations. Spatiotemporal interaction inside these clusters may further indicate some kind of wavelike process. Thus, whereas the first class of clusters could be an outcome of farmers' interacting and deciding collectively, the second class could be an outcome of rather passive observational learning.

Our test of hypothesis 2 has to be interpreted with caution, because the analysis suffers from the relatively low number of observations for the comparison of cluster members with their non-cluster counterparts. However, we still find evidence for three out of five clusters consisting of members characterized by relatively larger production quantities. Further, the fact that the largest cluster showed a significantly higher upper quartile may even provide evidence for the existence of role model farmers inciting other farmers to switch as well. Thus, the hypothesis is supported in those cases where an analysis was appropriate.

The creation of the spatial price proxies reveals some interesting insights into the relation between switching decisions and relative prices. First, we observe that in the years with lower relative prices paid by the competitors, fewer members leave the cooperative. The years characterized by higher prices are also characterized by a higher spatial heterogeneity of the relative prices and the detection of more spatiotemporal clusters. Additionally, we see a relatively clear relationship of the favorability of local competitors' prices and the existence of spatiotemporal clusters for the fourth year, which supports hypothesis 3. However, the first three years do not show such a relationship, which could be due to the lower spatial heterogeneity of prices or the construction of the spatial price proxies.

Conclusion and further research

To our best knowledge, the article presents the first analysis of the spatiotemporal interrelatedness of farmers' switching decisions and sheds light on farmers' actual behavior from a different and innovative perspective. Gaps of the extant literature are filled and rather neglected issues are raised by using methods that are relatively new in economics. Generally, the findings underline the issue of endogeneity in the data generating process. Furthermore, we find two classes of spatiotemporal clusters, which likely underlie different social and/or economic processes. Evidence for a relationship between spatiotemporal clusters and pricing as well as the farmers' production volume is provided. These insights may contribute to future research.

The empirical approach used to test the hypotheses in question has several important limitations. The most important refers to the fact that we only gather data from one cooperative. Thus, the processes inside the supplier base of that cooperative cannot be generalized to supplier bases of buyers of agricultural products per se and are rather restricted to that cooperative and/or sector under consideration. Additionally, the resulting point patterns per year are with respect to the first three years under consideration relatively low. Therefore, clusters obtained by the STPSS may be a result of the heterogeneous underlying population at risk, rather than a real excess of spatiotemporal interrelated switching decisions. Thus, the consideration of an actual population at risk could have improved the results of the analysis. The same holds for the tests and conclusions based on the comparison of cluster members and their non-cluster counterparts. A larger number of switchers would imply better prerequisites to test for statistical differences. The construction of the price proxies can also be criticized, because uniform pricing and equal catchment areas for each competitor seem rather unrealistic. However, these drawbacks root in the highly confidential dataset, which naturally comes with certain weaknesses. Hence, testing for the relevance and existence of the hypotheses should be part of future empirical work in that area.

Generally speaking, the methods used could be employed in other settings or behaviors, where collective actions can be expected. Availability of data on actual behavior should be used more often in research to avoid biases based on elicitation methods wherever possible. This may leverage the understanding of economic decision-making. Nevertheless, the understanding of the observed behavioral data can also profit from experimental economics in testing hypotheses regarding the data generating process with respect to social interaction and contagion.

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