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Exploring the Spatiotemporal Dynamics of Cooperative Members' Switching Decisions

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ABSTRACT

This article analyses the spatiotemporal dynamics of the actual switching behaviour of farmers' in a dairy cooperative's membership base. Space-time permutation scan statistic is used to identify clusters of switching decisions in space and time, while objective and publicly available indicators are related to the occurrence of these clusters. The analysis reveals two classes of clustered switching decisions: Clusters in which many farmers switch on a particular day and clusters covering longer periods of time with farmers switching in a herd-like pattern. Additionally, the relationship between farm sizes as well as price incentives and clustered switching decisions is observed. [EconLit citations: Q13; C23; L25].

Keywords: *supply base dynamics; spatiotemporal clustering; space-time permutation scan statistic*

1 Introduction

Tremendous evidence has been compiled regarding the deterioration of relationships between cooperatives and their members in recent years (Burt & Wirth, 1990; Fulton & Giannakas, 2001; Hogeland, 2006; Nilsson et al., 2009). Competence-based managed problems and general disadvantages of the organizational structure serve as the primary reasons for the distorted relations (Cook, 1995; Hansmann, 1988; Nilsson, 2001), ultimately resulting in lower economic performance, as well as the alienation of members and representatives due to growth and increased member heterogeneity (Fulton & Giannakas, 2001; Nilsson et al., 2012). These problems lead to increased fluctuations in membership, further inducing costs for suboptimal capacity utilization and a costly acquisition of new suppliers. In extreme cases, a crumbling supplier base could precede the buyer's demise if increasing numbers of defecting suppliers develop their own dynamic, resulting in a vicious circle of supplier fall-out (Nilsson et al., 2012). Accumulated switching decisions, i.e., many farmers leaving their processing cooperative in order to trade with another buyer, imply a high risk for cooperatives. Assuming that switching decisions are driven by incentives which vary over space and time, the occurrence of such spatiotemporally accumulated switching decisions can be deemed likely.

At the farmer level, a switching decision indicates a farmer's expectation to receive better conditions from another buyer. Such expectations are formed, among others, through information acquired from media or other farmers, i.e., a farmer's social and professional network. This information can include the observation of others' switching behaviour or more specific information related to underlying reasons. Assuming contagious effects, as in the case of innovation adoption (Rogers, 1995), increased numbers of defecting suppliers could indicate the beginning of a vicious circle of supplier fall-out (Hirschman, 1970; Nilsson et al., 2012).

Despite its practical and theoretical relevance, however, the interrelatedness and consequently the dynamics of farmers' actual switching decisions has not yet been investigated.

This article seeks to fill this research gap using a unique dataset of the actual switching behaviours of cooperative members in space and time. It is thus hypothesised that farmers' switching decisions are spatially and temporally interrelated, and that this interrelation can provide meaningful insight, especially for buyers of agricultural raw materials. This is particularly relevant for those buyers that are organized as cooperatives with an inherent interest in a stable supply base. Given the substantial complexity regarding cooperatives' membership bases, this evaluation aims to identify typical patterns of switching decisions in space and time. Of particular interest is whether, and to what degree, farmers' switching decisions accumulate across space and time, as well as how that relates to objective and easily available indicators such as price relations or farm size. In order to meet this research gap, it is crucial to identify characteristic patterns of switching behaviour. Insights obtained from the observation of the interrelatedness of farmers' switching decisions should help to obtain a better understanding of the underlying dynamic processes and generate new testable hypotheses which may contribute to the literature on farmers' switching behaviour.

The remainder of this article is organized as follows. First, a discussion is presented regarding the existing literature on farmers switching decisions, as well as its limitations with respect to data on actual behaviour and dynamic processes. The formulation of hypotheses for the spatiotemporal characteristics of switching decisions is based on several theoretical rationales and is succeeded by a description of the data and methods. Finally, the results are presented and discussed, followed by the conclusions regarding practical implications and the need for future research.

2 Empirical studies on farmers' switching decisions

Despite an enormous body of literature dealing with business relationships, little empirical work has focused on (farmers') actual switching decisions. The majority of existing articles mentioning farmers' buyer switching decisions appear in the context of agricultural cooperatives, underlining the particular relevance of the issue for this legal entity. Extant studies primarily gather data by means of surveys and use various kinds of operationalisations of switching decisions which can be roughly divided into two categories: The first includes potential switching decisions as cooperative members' readiness or intention to abandon the buyer (Bhuyan, 2007; Hernandez-Espallardo et al., 2013; Schulze, 2006). The second category deals with 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 & Bentancor, 2005). The objectives of these articles range from the analysis of human values (Feng et al., 2011) or motivating factors behind farmers' loyalty to their cooperative (Morfi et al., 2015) over the question of how attitudes and beliefs shape farming members' behaviour (Bhuyan, 2007) to factors associated with the choice of cooperative versus proprietary milk handlers (Jensen, 1990). Major determinants of switching intentions, or loyalty (as the positive perspective), include satisfaction with collaboration (Schulze, 2006), information or prices (Feng et al., 2011; Hernandez-Espallardo et al., 2013; Morfi et al., 2015; Zeuli & Bentancor, 2005), as well as participation in the cooperative (Bhuyan, 2007). Hansen et al. (2002) provide further evidence for the relevance of group cohesion in cooperatives.

Upon review of the extant literature on farmers' switching behaviour, three important research gaps can be identified; the present study attempts to overcome these gaps. First, there is a general lack of information on actual switching behaviour. 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-behaviour gap, as well as recall bias. Second, the studies typically refer to price satisfaction or general satisfaction with the performance of the business relationship rather than real prices and/or price differences. Farmers' decisions, on the other hand, are often based on subjective perceptions and social influence; factual conditions, e.g., prices paid to farmers, underlie these perceptions and may be easily adjusted by the cooperatives' management. Third, despite reports about high numbers of farmers switching at the same time (e.g., Dermody, 2015) and so-called bank runs reported in the literature (Nilsson et al., 2012), which suggests interdependence of switching decisions among farmers, a thorough investigation of this phenomenon is lacking empirical support. This is further impacted by cross-sectional studies' inability to test for system dynamics.

3 Analysing switching decisions in space and time

In this article, a switching decision means that a farmer chooses to discontinue a business relationship to trade with a new buyer from a more or less distant future point in time. Farmers are understood as being decision-makers under uncertainty who are subject to incentives which can be assumed 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. Such examples have been demonstrated, e.g., by Lines and Westerhoff (2010) for inflation expectations or by Baak (1999) for price expectations on cattle markets. In the following, it is explained how space can be understood as a proxy for the decision context, i.e. incentives, as well as for the information flow and thus the formation of expectations throughout established networks. Softer factors such as commitment or trust, which have previously been shown to affect switching intentions, have been explicitly excluded. This is not to say that these factors are not important, rather that the purpose of this analysis is to develop a model which relies on objectively observable variables that are easily available for cooperatives' decision-makers.

3.1 Space as a determinant of the decision context

It is then assumed that the spatial location and the time in which a decision takes place, 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 prices) and farm characteristics, as well as additional factors influencing production decisions and profitability. Since most of these factors also vary over time, the individual farmer has to deal with a constantly changing environment and information base for the switching problem. It can be argued that the complexity relating to the 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, p. 236). This rather vague law with respect to space can be extended to include both space and time (Miller, 2004). Hence, neighbouring 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 will likely imply an increased probability of a neighbouring farmer to make a switching decision due to the similarity of the objective environment.

3.2 Space as a determinant of social networks

In addition to the rationale behind the spatiotemporal determinant of switching decisions, it is crucial to remember that an economic-focused decision maker is also influenced by other decision-makers (Banerjee, 1992; Manski, 2000). 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 are in turn determined by spatial proximity (Butts, 2002; Liben-Nowell et al., 2005). Hence, it can be assumed that a spatial relatedness of farmers' decisions based on their social networks provides a rationale for the impact of a neighbourhood (Ellison & Fudenberg, 1993) or neighbouring farmers (Foster & Rosenzweig, 1995) on farmers (switching) decisions. This impact may happen directly through communication or indirectly through observation.

3.3 Spatiotemporal dynamics in the farming supplier base

Many firms spend a lot of time and effort to predict and control their supply system, but struggle with its dynamics and complexity (Choi et al., 2001). Complex systems that consist of networks of interacting actors have a dynamic and aggregate behaviour which evolves from the individuals' activities. This aggregate behaviour, sometimes termed as 'emergence' (Harper and Lewis 2012), can be described without detailed knowledge of the behaviour of the individual (Holland & Miller, 1991). Examples for such events of emergence in the context of economic interaction are demonstrated by knowledge spillovers or herding behaviour (Harper & Lewis, 2012). Acknowledging the aforementioned processes, the decision-making not only takes place in particular spatiotemporal contexts, but also "generates spaces and times with variable reaches and intensities" (McCormack & Schwanen, 2011, p. 2802). Taking into account this endogeneity, a spatial-dynamic process that links economic actors over space and time can be observed (Wilen, 2007), making the prediction and control of switching decisions a difficult task. However, spatiotemporal processes are supposed to generate patterns that can be potentially predictable (Wilen, 2007).

The distance in space and time reflects a general likelihood of relation and interaction within the network, which causes, in combination with the contextual factors, the emergence of observable spatiotemporal patterns: The similarity of incentives increases the likelihood that neighbouring farmers will switch within a short period of time. Furthermore, the switching behaviour could also drive other farmers to switch as a result of social interconnection.

Knowledge about the existence of emergence at the micro-macro link in relation to switching decisions, may help to better understand the processes which ultimately lead 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, this article aims to shed 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.

3.4 Hypotheses

Considering the complexity and dynamics that decision-makers face, it is necessary to analyse patterns of cooperative members' actual behaviour in space and time; this can be achieved by specifically identifying typical patterns of switching decisions. The patterns in the supply base can deliver hints of the underlying data generating processes. Here, an attempt is made to evaluate the extent of group-like switching decisions, i.e., how decisions are interrelated across space and time, and to describe the relationship between such phenomena and objective indicators potentially available to a cooperative.

Given the explanations in the previous sections, the following hypotheses can be formulated: First, since farmers near to one another in space and time face similar contextual factors and have the tendency to have an effect on each other, one can expect that switching decisions are highly interrelated across space and time. Such a degree of interrelation will result in spatiotemporally clustered switching behaviour, which can further be described and analysed. Therefore, it can be hypothesised that:

H1: There are spatiotemporal clusters, i.e., whole groups of switching farmers in relative spatial closeness and within 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 overall emergence. 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 relationships and encourage them to switch as well. Furthermore, a large traded volume may imply a large farm size or specialization in the respective area, which could imply that those farmers serve as local opinion leaders. Hence, provided that the existence of spatiotemporal clusters can be shown, it can be hypothesised that:

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

Another area of interest is the effect of prices on switching decisions. While previous research has shown that many factors, including trust and loyalty, prevent farmers' immediate switching to another buyer due only to price differences, it can be assumed that those farmers who do switch have done so in response to price signals. The nature of the existing research has made it impossible to relate actual switching behaviour to actual prices and price differences between competing buyers. It is therefore hypothesised that:

H3: The more favourable the pay-out of local competitors when compared to farmers' current buyer's pay-out, the more farmers will switch to another buyer.

4 Empirical strategy and data

These hypotheses are tested by means of a unique dataset with actual switching decisions, covering a four-year period. The switching decisions are geographically referenced and temporally tagged, leading to a dynamic point pattern which allows for the use of spatiotemporal tools and statistics. There are two standard methods employed for the analysis of spatial point patterns (Haggett et al., 1977; Upton & Fingleton, 1985). One method uses test statistics based on measures of distances derived from the information related to spacing of points in order to characterize the pattern. The other method is area-based and analyses the variability of points in certain subsets of the space under investigation. Since this investigation is interested in the actual spatiotemporal locations and compositions of clusters, while lacking prior knowledge of the relevance of metric distances, as well as the size or the composition of accumulative switching decision, it is necessary to use 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 fulfil 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 the current 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 for the detection of 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 fields, such as criminology or epidemiology, because they may indicate certain data generating processes or point to emerging trends (Tango, 2010). In line with the objectives, an effort is made to identify such clusters in order to describe them and relate them to farmers' characteristics, as well as external factors affecting switching decision.

4.1 Space-Time Permutation Scan Statistic

The following provides an introduction of the functionality of the STPSS as developed by Kulldorf et al. (2005). The STPSS belongs to a broader family of spatial and space-time scan statistics. Generally, 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 have since been developed and widely applied in various disciplines, namely epidemiology, ecology, criminology etc.. Scan statistics essentially uses a scanning window that moves across the dimensions of interest. In the spatial setting, a mostly circular window is 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 so that instead of varying circles across space, varying cylinders are used. While 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 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, size and/or timespan. However, the large quantity of potential clusters implies a multiple testing problem. Thus, the statistical significance of the cluster under consideration is evaluated while taking this problem into account (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 is elaborated on in the following, in accordance with the article by Kulldorff et al. (2005).

The study area and time period of interest are initially subdivided into areas *(z)* and time periods *(d)* to assign and aggregate the points or cases. The areas are defined 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 typically 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 thus be calculated as:

$$C = \sum_z \sum_d c_{zd} \tag{1}$$

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

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

In this case, the formula corresponds to the proportion of all switching decisions that occurred in area *z*, multiplied by 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:

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

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

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

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

4.2 Data and background information

The dataset used for this analysis was obtained from a large European dairy cooperative. The dairy sector is characterized by highly interdependent and typically long-lasting relationships between the farming and the processing levels where cooperatives traditionally play an important role (Bonus, 1986). Furthermore, the spatially dispersed production of the raw product and the costly shipping fees for perishable milk, for example, underline the importance of the spatial dimension for the analysis of dairy cooperatives (Graubner et al., 2011). The data is comprised of a total of 1,236 switching decisions, i.e., farmers leaving the cooperative in order to trade with another buyer, over a four-year period. The individual switching decisions are temporally (day of receipt of termination) and geographically (municipality) referenced and further complemented by the farmer's production/traded volume. It is important to note that members of the dairy cooperative are tied to delivery obligations, meaning that they are obliged to ship all produced milk to the cooperative's dairy. Such intake/delivery obligations are a common regulation for dairy cooperatives (Schlecht & Spiller, 2012), typically resulting in a strong dependency on the prices paid by the cooperative since the farmers cannot split the deliveries.

The competitors' and the cooperative's annual average market prices were gathered from an agricultural statistics provider. The cooperative in question employs a uniform pricing policy across the catchment area, where the cooperative bears the costs of transportation from the farm to the processing facilities. Uniform pricing results in uniform prices across the catchment area and is a rather common practice among cooperatives (Durham et al., 1996; Greenhut, 1981); moreover, uniform pricing is the prevalent pricing policy of the dairy market under consideration.

Each farmer in the dataset only switched once during the study period; furthermore, farmers who completely quit production are excluded from the sample. Typical for cooperatives and according to the dairy cooperative's statutes, the termination notice has to be handed in prior to the end of a calendar year to end the business relationship two years later (BKA, 2012). Hence, all members deciding to switch buyers during the course of each year effectively leave the cooperative on the same date, i.e., the first of January, two years later. Prices for raw milk are not fixed ex ante and are generally a consequence of the economic performance of the respective dairy at the respective time (BKA, 2012). In combination with highly volatile world markets for dairy products, farmers face a tremendous amount of uncertainty regarding future prices paid by the cooperative or potential competitors. Consequently, assuming rational decision-making and well-functioning markets for raw milk, one would expect the majority of member defections to take place at the end of each year as this keeps all opportunities open and may reduce the risk of making a bad decision.

The market for raw milk, however, is far from perfect (BKA, 2012). Relatively high transportation costs limit the dairies' catchment areas, which further fragments the market for raw milk into smaller subsets, ultimately resulting in heterogeneous switching opportunities for the cooperative members across space and time. Whiles some farmers in the membership base may face several switching opportunities, others may lack the option of switching to any competing dairy. Thus, all farmers in the membership base do not represent the actual population at risk since not every farmer in the membership base is actually at risk of switching to another dairy due to limited switching opportunities. Hence, it seems reasonable to restrict the analysis in the dairy sector solely to the spatial distribution of actual switching decisions taking place in the membership base and further omitting the underlying distribution of cooperative members. In the STPSS-model, it is assumed that the function generating the switching decisions operates uniformly across all time-periods and area subdivisions (Kulldorff et al., 2005). Detected clusters may therefore be a result of either increased switching activity or a different geographical underlying membership distribution at different times. To reduce the influence of the latter, the STPSS is applied to each year separately.

Switching decisions referenced with the exact dates of notice during the four-year period of interest provide the unique opportunity to analyse temporally dispersed decisions that lead to the same outcome in terms of effective termination. Since the membership dynamics in cooperatives' membership bases in general and in dairies specifically, are not fully understood, an exploratory analysis of switching decisions in space and time during the course of different years might help to detect new phenomena, which may lead to a greater understanding of cooperatives and the raw milk market alike.

As previously mentioned, however, farmers near to one another in space and time tend to face similar contextual factors, which may lead to the emergence of interrelated switching decisions. Since the focus of this analysis lies on the understanding of economic/market aspects leading to switching decisions, other factors that could lead to an increased risk of switching in a spatiotemporal subset should be taken into account. In the context of agriculture, the most important factor is likely that of local climatic conditions, which have a substantial effect on working schedules. Certain climatic conditions, inter alia intense rainfall, may force farmers in a given region to work indoors and potentially to engage in office work during affected times, which could result in an outburst of switching decisions. To control for space-time interaction due to climatic conditions, data were gathered from Germany's National Meteorological Service (DWD, 2015); more specifically, data indicating soil moisture and soil frost that is gathered on a daily basis was utilized.

For the sake of confidentiality, it is not possible to provide more detailed information on the dairy cooperative. The data has therefore been masked when necessary and descriptions are based on aggregates; moreover, additional background information is not provided in order to secure data privacy.

5 Analysis and results

The 1,236 switching decisions were gathered over a span of four years, with the fourth year containing over 50 per cent of all cases collected from the study period. The distribution of switching decisions during the course of each year 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 the greatest amount of switching decisions occurring in December. No cases are recorded of such decisions being made over the weekend. Furthermore, there is no particular day of the week in which switching decisions are more likely to occur.

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 that is nearly twice the size of the Netherlands. In that context, it is important to mention that the random assignment of switching decisions introduces inaccuracy on the municipality level. However, with a total of 2,195 municipalities in the convex set and a total of 338 municipalities being subject to a switching decision, the STPSS is known to adequately take such common data deficiencies into consideration (Malizia, 2013).

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

5.1 Implementation through SaTScan™

To control for potential space-time interaction caused by climatic conditions affecting the farmers' work schedules and consequently the time of switching decisions, the nearest neighbouring measurement station was assigned to each location of a switching decision. This procedure assigned each switching decision to one of 98 different measurement stations providing data on soil moisture and frost on a daily basis. In the STPSS, the covariate adjustment is made at the randomization stage of the procedure where each covariate category is independently randomized (Kulldorff, 2015). A binary is therefore necessary to indicate the presence/absence of the covariate in question. The binary was created based on certain thresholds for the indicators for soil moisture and soil frost. Here, if the mean daily soil temperature in 10cm depth for uncovered typical soil fell below zero degrees Celsius, the binary for soil frost was set to one. If the indicator for soil moisture under grass and sandy loam between 0 and 10 cm depth in % plant useable water exceeded 100, the binary for soil moisture was set to one. Missing values, i.e., no reported parameters for the measurement station corresponding to the switching decision on the days in question, were set to zero.

Table 1 provides an overview of the respective parameters of the climatic conditions associated with the switching decisions.

Table 1.
Climatic conditions associated with switching decisions

	Year 1	Year 2	Year 3	Year 4
Switching decisions	189	182	224	641
Soil frost (absolute; proportion)[1]	2; 1.06 %	0; 0.00 %	2; 0.89 %	18; 2.8 %
Soil moisture (absolute; proportion)[2]	141; 74.60 %	147; 80.77 %	146; 65.18 %	293; 45.71 %
Missing Values	7	3	0	0

[1] Indicates numbers of switching decisions with soil frost (10cm depth, uncovered soil) at the locations of the switching decision on the respective day.
[2] Indicates numbers of switching decisions where soil moisture under grass and sandy loam between 0 and 10 cm depth in % plant useable water exceeded 100 at the location of the switching decisions on the respective day.
Source: Authors' calculations based on weather data obtained from DWD (2015)

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

Table 2 shows the characteristics of the detected spatiotemporal clusters controlling for space-time interaction caused by climatic conditions, ranked by years and pseudo significance values. Seven out of ten clusters refer to the fourth year under investigation, in which there was an overall high proportion of switching decisions. For years one, two and three, only a single cluster could be detected for each year, respectively. The radiuses of the obtained clusters range from 11.01 to 99.71 km. Furthermore, the clusters consist of between 5 and 104 switching decisions. Four out of ten clusters cover only one single day. The maximum temporal length is more than five months.

The clusters which are limited to a single day lack an inner temporal component due to days being the smallest temporal units. However, the clusters spanning a longer period of time can be further analysed regarding their spatiotemporal pattern. Here, the Mantel test (Mantel, 1967), which tests for overall space-time interaction, was used. In one (cluster 4) out of every five clusters, the null hypothesis of spatiotemporal randomness could be rejected, indicating a statistically significant association of space and time in the appearance of switching decisions within the clusters.

Table 2.
Summary of the detected spatiotemporal clusters (controlling for climatic conditions)

Cluster	Year	Radius (km)	Start Date	End date	p-value	c_A	μ_A
1	1	11.01	6th January	6th January	0.001	5	0.26
2	2	27.91	3rd November	3rd November	< 0.001	16	1.74
3	3	20.12	2nd January	2Nd January	< 0.001	27	6.89
4	4	47.96	16th August	4th October	< 0.001	104	43.15
5	4	21.35	6th February	27th June	< 0.001	29	7.49
6	4	12.38	10th July	1st August	< 0.001	9	0.43
7	4	99.71	14th May	6th November	< 0.001	8	0.43
8	4	28.08	15th October	1st November	0.001	31	10.33
9	4	38.62	8th October	8th October	0.023	9	0.81
10	4	53.20	6th November	17th December	0.047	26	8.82

Clusters sorted by year and significance (p-value)
c_A: Observed number of switching decisions within the cluster
μ_A: Expected number of switching decisions within the cluster
Source: Authors' calculations

5.2 Farm size and switching behaviour

The problem of spatial heterogeneity arises when comparing the farmers' characteristics within a cluster to the farmers' characteristics outside a cluster. 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, the average production volume of farmers inside a cluster can be compared to the production volume of other farmers switching in the same area and year, effectively reducing the bias of spatial heterogeneity.

However, this approach significantly lowers the subpopulation that can be compared to a given cluster. Only four clusters (clusters 4, 5, 8 and 10) can be evaluated meaningfully in comparison to their non-cluster counterparts, i.e., clusters that consist of at least ten observations for the area during, as well as outside the cluster period. Table 3 depicts the descriptive statistics regarding the distribution of switching farmers' production quantities for each area inside and outside the cluster period.

Table 3.
Production quantities in kg/year of cluster/non-cluster switchers

	Cluster 4		Cluster 5		Cluster 8		Cluster 10	
	Inside period	Outside period	Inside period	Outside period	Inside period	Outside period	Inside period	Outside period
Mean	534,100	488,200	461,500	366,900	479,500	435,900	597,800	597,700
Median	486,100	485,400	443,600	278,800	450,00	402,400	557,000	566,900
Std. dev.	260,725	208,909	171,866	270,167	140,318	219,207	299,512	293,427
Switching Farmers (n)	104	91	29	10	31	52	26	36

Source: Authors' calculations

For all four clusters under consideration, the mean values of the production quantity are larger for farmers switching during the cluster period. The median production quantities are larger for clusters 4, 5 and 8, but not for cluster 10. The comparison regarding central tendencies was tested using the Wilcoxon Rank Sum Test. Results indicate that for cluster 5 ($p < 0.05$), the farmers' production quantities inside the cluster were significantly higher than the production volume of farmers outside the cluster.

5.3 Implementation of price incentives

In order to include the influence of prices on accumulated switching decisions in the analysis, it is necessary to have a local price incentive representing the relative financial superiority of switching for each switching farmer at the respective time. To calculate such a proxy for any given farmer, the switching farmers' relevant competitors for each federal state (according to the agricultural statistics provider) in the spatial point pattern of switching decisions are localized and added to the cartographic material. Then, the three nearest neighbouring competitors*, out of 71 competitors in total, were assigned to each switching decision, respectively. Based on the annual prices for the neighbouring competitors, an average price differential was calculated for each switching farmer by subtracting the annual average price paid by the cooperative from the average of the three nearest neighbouring competitors' prices. This procedure provides a price proxy which represents the yearly average switching farmer specific incentive to switch indicated by relative prices. A price differential of zero implies that the prices paid by the cooperative equals the average price paid by all relevant competitors for the switching farmer. The higher the price differential, the higher are the competitors' prices compared to the cooperative's prices. Consequently, a higher price differential represents a stronger economic incentive for a farmer to switch to another buyer. Table 3 provides an overview of the distribution of price differentials in Euro Cents per kilo raw milk amongst the switching farmers for each year, whereby the price differentials are based on the full sample, i.e., all locations of switching farmers over the four years. The rationale for calculating descriptive statistics on price differentials based on the locations from the full sample is rooted in the assumption that the point pattern, consisting of all locations of switching farmers, represents the spatial spread of the cooperative's membership base. Consequently, price differentials for the full sample may allow for a more suitable comparison of the price incentives that affect the membership base.

Table 4.
Relative price differentials, switching decisions and clusters detected annually across all locations of switching decisions

	Year 1	**Year 2**	**Year 3**	**Year 4**
Indicators (n)	1236	1236	1236	1236
Mean price differential	0.686	0.564	0.723	2.843
Median price differential	0.700	0.833	0.800	3.000
Min price differential	0.000	- 0.750	- 0.350	0.300
Max price differential	1.533	1.367	1.550	4.167
Std. dev. price differential	0.254	0.470	0.476	0.852
Clusters detected	1	1	1	7

Source: Authors' calculations

Table 4 shows that during year four, characterized by higher competitors' relative prices and a higher standard deviation of prices across the locations of switching farmers, more farmers decided to switch and more clusters can be detected. On the contrary, years one to three are characterized by lower mean price differentials for the competitors associated with fewer farmers switching and only a single cluster being detected.

In order to investigate the question of whether the clustering of switching decisions is associated with the local price differentials faced by the switching farmers, the relative price differentials of switching decisions are subdivided into two groups, i.e., the price differentials of the farmers located inside and the price differentials for farmers located outside the spatial windows of clustered switching decisions. This means that the statistics calculated for the price differentials inside the cluster areas are based on all locations of switching decisions that took place in the area of the respective cluster and the respective

* It was decided to use not only the best competitors' price in the respective year, but rather the three nearest neighbours' prices because the processor with the highest pay-out does not necessarily acquire more suppliers.

year. The price differentials for the locations of switching decisions outside the cluster areas are calculated based on all switching decisions that take place outside the cluster areas in the respective years. Hence, the temporal dimensions of the clusters are neglected in the calculations. Table 5 presents the descriptive statistics for each cluster and the two subgroups per year.

Table 5.
Annual relative price differentials of switchers in cluster/non-cluster area

		Cluster area:			**Non-Cluster Area:**		
Cluster	**Year**	**Mean Price differential**	**Median Price Differential**	**Switching decisions**	**Mean Price differential**	**Median Price Differential**	**Switching decisions**
1	1	0.738	0.733	7	0.648	0.700	182
2	2	0.308	0.367	16	0.841	0.833	166
3	3	0.335	0.350	27	0.958	0.950	197
4	4	3.577	3.700	195	2.600	2.900	191
5	4	3.300	3.300	39	2.600	2.900	191
6	4	2.912	3.000	16	2.600	2.900	191
7	4	1.712	1.700	20	2.600	2.900	191
8	4	3.077	3.000	83	2.600	2.900	191
9	4	1.017	1.150	35	2.600	2.900	191
10	4	2.140	2.267	62	2.600	2.900	191

Source: Authors' calculations

In exactly half of the clusters, the mean and median price differentials for the farmers located in the area of the cluster are lower than the price differentials for the farmers located outside the cluster-regions. In the other half of the clusters, however, the mean and median price differentials for switching farmers located inside the area of the clusters are higher than the outside of the areas of the clusters. The Mood's median test was employed to test these differences; results indicate that all differences in central tendencies are significant ($p<0.05$).

6 Discussion

The application of the STPSS for each year revealed spatiotemporal clustered switching decisions in three out of four years, which supports hypothesis 1. Not surprisingly, given relatively few switching decisions in the first three years, only a single cluster could be detected for these years, respectively. In year four, however, with a total of 641 switching decisions, seven clusters were detected. Since the STPSS detects clusters in the spatiotemporal distribution of cases, a larger amount of cases, i.e., switching decisions, are more likely to provide relevant results. Consequently, year four provides the greatest evidence for the actual occurrence of clustered switching decisions.

In year four, 216 out of 641 switching decisions are associated with a spatiotemporal cluster. Thus, the majority of switching decisions spatiotemporally interrelate with other switching decisions, emphasising the relevance of local dynamics within the membership base. In years where competitors pay much higher prices, cooperatives could potentially face local outbursts or shocks with a large numbers of farmers switching in a relatively short period of time.

The clusters appear to be relatively narrow in space and time and can further be classified into two types: First, there are spatiotemporal clusters where a group of farmers located near one another switch on a particular day (clusters 1, 2, 3 and 9). Second, there are clusters in which switching lasts for more than one day and farmers switch gradually within a typically larger area. Of these clusters, the patterning of the largest cluster both in terms of number of switching decisions and spatial extent (cluster 4) 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 may result from the relatively low sample sizes (Scheiner & Gurevitch, 2001).

The constructed binaries which indicate climatic conditions that may have an effect on farmers' working schedules allowed for testing for clusters that are not caused by a space-time interaction of climatic conditions. Consequently, the detected clusters face a similarity of contextual factors likely resulting from local market conditions and processes. There may be, e.g., two social processes that could have led to the existence of these two classes. The clusters or group-like switching decisions taking place on a particular day may be the outcome of a collective decision made 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, effectively changing their expectations and ultimately driving them to switch as well. Spatiotemporal interaction within these clusters may further indicate some kind of wavelike process. Thus, while the first class of clusters could be an outcome of farmers' interacting and deciding collectively, the second class could be an outcome of a more passive observational learning effect. However, other processes may also have led to the emergence of these patterns. The clusters spanning over a longer period of time could result from the activities of a competitor. In fact, a procurement officer of a competitor could gradually convince farmers in a specific region to switch to the competitor. Moreover, in line with the substantial transportation costs in the dairy sector, a farmer may simply have the chance to switch to another competitor because a neighbouring farmer had already switched to that competitor. Since dairy cooperatives usually bear the costs of transportation from the farm to the processing facilities, it is more efficient for them to enlarge their supply base in this area and collect from more than one individual farmer.

The test of hypothesis 2 suffers from the relatively low number of observations available for the comparison of cluster members with their non-cluster counterparts. As hypothesised, however, one cluster is comprised of members that are characterized by relatively large production quantities.

The creation of the local price differentials reveals some interesting insight into the relationship between switching decisions and relative prices. First, it can be observed that in the years with lower price differences between the cooperative and the competitors, fewer members leave the cooperative, supporting hypothesis 3. However, while an overall relationship between local price differences and the emergence of switching decisions can be assumed, there is not enough evidence to make any inference as to the occurrence of spatiotemporal clusters and the extent of the price differentials. Specifically, a relationship of the favourability of local competitors' prices and the existence of spatiotemporal clusters is found for five out of the ten clusters. Since the other five clusters show no relationship between the price differential of local competitors' prices and spatiotemporal clusters, however, it cannot be assumed that areas with relatively unfavourable prices experience clustered switching decisions more frequently. These findings may also result from the use of annually aggregated milk prices, meaning that the pricing data on a yearly basis does not match the phenomena of interest. Unfortunately, insights based on this relationship are limited.

7 Conclusion and further research

While striving for better performance remains the top priority for any company, a better understanding of the dynamics of farmers' switching behaviour could enable cooperatives to more effectively work against herd-like exits and reduce the threat of entering a vicious circle of declining patronisation and performance. To our best knowledge, this article presents the first analysis of the spatiotemporal interrelatedness of farmers' switching decisions and sheds light on farmers' actual behaviour from a different and innovative perspective. By using space-time permutation scan statistic (STPSS), an explorative method that is popular in medical and veterinary research yet relatively new in economics, support for the existence of spatiotemporally clustered switching decisions of cooperative members can be established. The analysis also provides weak evidence for a relationship between spatiotemporal clusters and farmers' production volume, indicating that larger farmers (in terms of production quantity) tend to influence the emergence of local switching decisions. While there is a clear relationship between farmers' switching decisions and the size of the price differential between their current buyer and relevant local competitors, the available data do not allow to test for evidence of clusters being induced by particularly high price differentials.

Nevertheless, the empirical approach used to test the hypotheses in question has several noteworthy limitations. The most important of these limitations refers to the fact that data used for this analysis were only gathered from one dairy cooperative. Thus, the processes within the supplier base of that cooperative cannot be generalized to supplier bases of buyers of agricultural products and are rather restricted to that cooperative and/or sector under consideration. Moreover, the resulting point patterns per year are, with respect to the first three years, 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, for example, would imply better prerequisites to test for statistical differences. The construction of the price proxies can also be criticised. However, these drawbacks are the direct result of working with a highly confidential dataset. Thus, testing for the relevance and existence of the hypothesised behaviours should be an objective for future empirical work in that area.

Furthermore, there are two classes of spatiotemporal clusters, which may emphasise the role of different social and/or economic processes. However, the actual data generating process leading to these outcomes remains unclear. Future research should aim to explore the underlying processes, specifically by aiming to use data on actual behaviour wherever possible. Such empirical work may improve the understanding of economic decision-making. Nevertheless, the understanding of the observed behavioural data can also benefit from economic experiments in testing hypotheses regarding the data generation process with respect to social interaction and herd-behaviour. This is particularly important as more information regarding the spatial delimitation of actual networks and their behavioural impact could be obtained.

Finally, the methods used could be employed in other settings or for other behaviours, e.g., to predict innovation diffusion.

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