Technology Diffusion through Networks - Adoption of automatic milking systems in Germany

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Abstract:
As information about availability and suitability of innovation is one of the key factors in the diffusion and adoption of agricultural technology, its transmission is of crucial importance. Farming neighbors are often mentioned as the most significant origin of knowledge. However, various sources, like extension services, technology providing companies or other stakeholders are also possible in case of adoption of automatic milking systems in Germany. One instrument in describing the flow of information are social networks by defining links between different agents through which it can spread from one to another. Thus, different network structures, like a neighborhood network, a sales structure network, a dairy factory network and two extension service networks, are created to analyze their impact and performance in the process of diffusion and adoption of technology by displaying information transmission patterns originated from different sources to the farmers. For measurement, the endemic-epidemic hhh4 model for surveillance data is applied to capture the dynamic contagious process of diffusion. Regarding the performance, the neighborhood network provides the best fit for explaining the adoption of technology. Furthermore, the sales structure of the manufacturer also plays an important role in the distribution. In contrast, German consultation centers are less relevant.

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Abstract

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1) Introduction

Innovation and technology adoption are key forces pushing development and productivity growth in agricultural production (Conley and Udry 2010; Beaman et al. 2016; Läpple et al. 2015; OECD 2015) and therefore constitute a core area of research. To address this issue, the European Union, established the European Innovation Partnership ‘Agricultural Productivity and Sustainability’ (European Commission 2012). By providing this platform, the EU aims to bring together researchers and different stakeholders to facilitate diffusion and implementation of new technology in the agricultural sector.
Besides the characteristics of different adopter groups, especially factors driving technology adoption are of major interest. Classical literature in agricultural economics concerning this subject, emphasize farm characteristics (farm size, livestock, land ownership) economic (credit and labor availability, product and factor prices) and socio-economic (educational level, experience) factors (Feder et al. 1985; Foster and Rosenzweig 2010; Diederen et al. 2003) determining adoption or non-adoption. Nevertheless, already in 1943, Ryan and Cross identify social interaction as an important influence on adoption of new crop seeds. Lately, a wide range of literature suggest that adoption decisions of farming neighbors are additionally influencing the adoption behavior of individual farmers (Rogers 1995; Beaman et al. 2016; Case 1992; Lewis et al. 2011; Maertens and Barrett 2012). Neighbors are an important origin of information about new technologies, which is a key factor in the diffusion of new ideas and practices (Rogers 1995), but they also provide experience about the suitability and operation of new farming technologies. Yet, one can think of further sources providing information about new technologies, e.g. extension services, technology providing companies or other stakeholders involved in the production process. For measuring and analyzing such spillover effects which can facilitate technology diffusion and adoption, different ways are possible, like for example a spatial lag model or threshold models. A common model to analyze relationships in non-economic social science are networks (Maertens and Barrett 2012). Social networks can be used to define links between different agents, through which information can flow (Easley and Kleinberg 2010; Rogers 1995). Rogers (1995) calls these network links predictors of an individual’s adoption behavior. In particular, the network structure is considered to impact the diffusion and adoption of technology (Easley and Kleinberg 2010; Rogers 1995).

In the agricultural sector, milk production is often in the focus of public attention and especially in Germany highly important. Furthermore, milk, for the most part, is highly technological produced under the use of complex technologies. One innovation represents automatic milking systems (AMS). AMS are not only automatizing the milking process, but it can also impact the farm management as a whole (Meskens et al. 2001; Sauer and Zilberman 2012; Jacobs and Siegeford 2012; Eastwood et al. 2017). In 1992, the first AMS was installed on a dairy farm in the Netherlands (Eastwood et al. 2017; Sauer and Zilberman 2012). Although, different factors identified to determine the adoption of AMS (Meskens et al. 2001; Sauer and Zilberman 2012)
this study, is focusing on the influence and differences of several network structures in the diffusion process of AMS in Germany from 1997 to 2013.

The paper is structured as follows. In section 2 an overview of the literature about social effects on the adoption of technology in agriculture is given as well as the research question and the conceptual frameworks is spelled out. After the explanation of the data and some descriptive statistics (section 3), the methodology is shown (section 4), followed by results and discussion in section 5. Section 6 concludes.

2) **Background**

2.1) Literature review

Several papers study the influence of networks and neighbors on the diffusion and adoption of technology in agriculture, primarily in developing (Xiong et al. 2016; Conley and Udry 2010; Wollni and Andersson 2014; Foster and Rosenzweig 2010; Beaman et al. 2016; Maertens and Barrett 2012) and some few in developed countries (Läpple et al. 2017; Brown and Roper 2017; Diederen et al. 2003). In doing so, they focus on different aspects of technology adoption. While some target the way of learning from peers (Xiong et al. 2016; Conley and Udry 2010; Foster and Rosenzweig 2010), do others address differences between certain adoption groups (Deroian 2002; Watts and Dodds 2007; Lynn et al. 2017; Diederen et al. 2003) and their corresponding characteristics. Exceedingly, the influence of opinion leaders, or rather innovators, and early adopters appear to be of interest (Deroian 2002; Xiong et al. 2016; Watts and Dodds 2007; Lynn et al. 2017; Diederen et al. 2003). These groups are seen to be absolutely necessary for triggering the critical mass, which is essential to proceed the diffusion of technology (Rogers 1995).

In the process of successful adoption, different barriers must be overcome by the farmers. First, the individual needs information about the pure availability of an innovation (Rogers 1995). Additional, adoption is often associated with uncertainty (Xiong et al. 2016; Rogers 1995), as it can be described as a change of established procedures in production (Rogers 1995; Granovetter 2005), because the farmer has no or only little knowledge about use and profitability (Xiong et al. 2016; Foster and Rosenzweig 2010; Lewis et al. 2011) of the new technology. Thus, costs for the farmers arise, for seeking information and gaining knowledge. They cope with these costs by utilizing experiences and knowledge for neighbors, who are already using the considered
technology (Lewis et al. 2011; Foster and Rosenzweig 2010; Xiong et al. 2016). Xiong et al. (2016) summarize, transmission of information and knowledge is the major form of interaction of peers, e.g. as social learning. In different stages of the adoption process different information is needed and provided by close peers.

Different studies show geographically variations in the diffusion of new technology (Wollni and Andersson 2014; Larue and Latruffe 2009; Schmidtner et al. 2015; Lakner et al. 2011; Baptista 2000) due to agglomeration effects. As part of economic geography, agglomeration effects describe the implications of the concept of externalities by Marshall (Krugman 1993). Concentration of companies, working in the same field, in one area lead to the occurrence of three economic effects: the pooling of specialized labor, the improved supply of inputs and the facilitation of knowledge spillovers. Thus, geographically is associated with an improved awareness of innovation, reduced costs for information transfer and a more rapid spread of technologies (Baptista 2000; Porter 2000; Wollni and Andersson 2014).

Furthermore, social learning has proven beneficial, because farmers are more likely to adopt in the way of successful neighbors, as they demonstrate how to use new technologies under similar conditions (Sumane et al. 2017). It is also happening that farming colleagues share their impressions and possible gimmicks (Läpple et al. 2017). Sharing of information is more valuable and effective when it is done by a trustworthy person (Granovetter 2005, 1985). A study, for example, among farmers in New Zealand proves that farmers are trusting most other farmers (Small et al. 2016), which is another explanation for social learning being highly efficient, when farmers trained by near peers (Valente and Davis 1999). Some papers also suggest a more extensive, indirect effect by proclaiming influence of the neighbors of the neighbors of individuals (Läpple et al. 2017; Howard et al. 2011; Bramoulle et al. 2014).

A predominant portion of papers report a significant influence of neighborhood effects on the adoption decision and adoption performance of individual farmers. Foster and Rosenzweig (1995), for example show that farmers with experienced neighbors obtain higher profits and occur to have more land under new technology. In their study on pineapple production in Ghana, Conley and Udry (2010) find that social effects play a role in cultivation decisions, as farmers adapt their input use to the experience of neighboring farmers. Other studies confirm the dependence of individual decisions on the behavior of colleagues (Deroian 2002; Watts 2002;
Läpple et al. 2017; Valente et al. 2015; Case 1992). However, most studies focus on neighboring farmers, in the process of information diffusion, peers are not necessarily to be equated with farmers or relatives. As explained in the next section, there are different channels of information available to an individual farmer.

Despite all the additional factors, social spillover effects can contribute to the understanding of diffusion and adoption of technology, measuring the exact degree of social learning and social influence may be problematic. For example, it is of great importance to define carefully the neighborhood of each farmer (Conley and Udry 2010; Läpple et al. 2017), because lack of data can lead to a so called “missing neighbor problem” (Läpple et al. 2017) and to an over- or underestimation of relationships for individuals.

2.2) Research question and theoretical framework

Addressing such difficulties in measuring social effects, various econometric models are possible. Studies, for example, apply models analyzing spatial proximity (Läpple et al. 2015, 2016, 2017) or include the neighbor’s behavior in estimating profits of individual farmers (Foster and Rosenzweig 2010; Case 1992). Frequently used are threshold models (Diederen et al. 2003; Watts 2002; Watts and Dodds 2007; Meade and Islam 2006), which assume that individuals adopt, because a predetermined number of neighbors already adopted a certain technology. Howard et al. (2011) combine spatial proximity with a threshold model. Another possibility present game theory models (Montanari and Saberi 2010; Bramoulle et al. 2014). All these mentioned models have in common that they have a static look at the diffusion and adoption of technology. They often consider only one time period. In contrast, the word “diffusion” implicates a dynamic process, which can be compared to a kind of contagion pattern of diseases (Valente et al. 2015; Beaman et al. 2016; Easley and Kleinberg 2010). For this reason, the applied model must capture the contagious dynamic of the adoption process, as they are not only displaying spatial but also temporal effects. Two major kinds of contagion models are distinguished: SIR and epidemic models. SIR models indicate the three stages an individual can obtain in a contagion situation – susceptibility, infectivity and recovery – and are usually combined with threshold models (Watts and Dodds 2007; Liu and Zhang 2014; Easley and Kleinberg 2010). But these SIR models are not fully applicable to the diffusion and adoption of
technologies, because the stage “recovery” is usually not an option or depends on a wide range of (economic) factors. Additionally, focuses the considered process primary on the decision to adopt or not adopt. For this reason, an epidemic model fits best to capture the spread of social spillover effects in a dynamic diffusion and adoption process (Meade and Islam 2006; Valente et al. 2015; Beaman et al. 2016; Diederer et al. 2003; Easley and Kleinberg 2010).

Bringing together epidemic modelling and the spread of information as social effects in a technology adoption setting, networks can serve as an instrument (Funk and Jansen 2013; Grassi 2010; Easley and Kleinberg 2010). Networks are composed of nodes, which are presenting different agents, and links connecting these agents. These links equal channels of information, required in the decision-making process, flowing quickly from one agent to another (Delre et al. 2010; Valente and Davis 1999; Montanari and Saberi 2010; Easley and Kleinberg 2010). Networks can align the behavior of peers, by displaying the spread of ideas and innovations (Easley and Kleinberg 2010) over time and space. Thus, the network structure plays a key role.

Networks are very flexible constructs, which are defined by their structure. The network structure determines the spreading pattern of an epidemic process (Easley and Kleinberg 2010). Rogers (1995) confirms diffusion and adoption is facilitated or handicapped by structure of the social system. Hence, in the understanding of social spillover effects on adoption of technology the design of the social environment should be emphasized. Besides, neighboring farmers, also other sources of information about innovations are possible, however most studies focus on the influence of nearby peers (Xiong et al. 2016; Montanari and Saberi 2010; Beaman et al. 2016; Läpple et al. 2017) and do only pay less attention to other types of information patterns. Other channels of information flow, for example, are agricultural extension and consultation services (Conley and Udry 2010; Fritsch and Kauffeld-Monz 2008; Sumane et al. 2017; Läpple et al. 2016). In considering adoption of a commercial distributed technology, also the distribution and sales structure of the manufacture can be of interest (Fritsch and Kauffeld-Monz 2008), as well as other stakeholders of production involved in an information diffusion process (Sumane et al. 2017). This paper aims to analyze if agricultural technology innovation spread through network structures and to compare the influence different kinds of network structures in the adoption diffusion process.
3) **Data and descriptive statistics**

This study is based on a dataset of installed AMS in Germany by one manufacturer. The data provides the postal code, as well as the day, month and year of the installation. In total 3531 AMS in a time period from July 1997 to November 2013 are included. As the analysis is based on district levels in Germany per year, the postal codes are assigned to the respective districts and aggregated to a yearly basis.

Figure 1 shows the development of AMS of this manufacturer in the considered time period. While in year 1997 only six systems installed, there are 127 installed in 2007, with its peak in 2013 with 575 systems. Furthermore, the graph shows that the rate of diffusion seems to be very low until 2005 when it speeds up.

![Figure 1: Development of AMS-Installations, 1997 - 2013](image)

The low number of AMS in 2013 could emerge as not the whole year is represented in the dataset. This explanation is strengthened, because, considered monthly, AMS installations rather take place in the winter months. However, it is also conceivable that the adoption of AMS by this manufacturer decreases, for example because of increasing competition. But such a trend is incomprehensible by this dataset.
Additional, the dataset provides some insights in the variations in total numbers of installations between the federal states in Germany. Figure 2 shows that Bavaria (590 in total) and Lower Saxony (573 in total) are leading the list. The two city states Hamburg and Berlin have no recorded AMS. Furthermore, there is a difference noticeable between Western and Eastern Germany. While in Western Germany about 86% (2186 in total), only about 14% of AMS are installed in the Eastern states.

After lightning variations between the single federal states, occurring differences within the federal states are presented in Figure 3. The map of Germany is divided into the 402 districts. The diverse colors display the total number of aggregated AMS over the considered time period. 142 districts have no reported installations (white) and most districts (194) have less than 10 (light green) from 1997 to 2013. However, the red and dark red colors demonstrate, that 11 districts have more than 40 installations, with Kleve (77 in total) and Ravensburg (76 in total) with more than 70 installations. According to the results of Figure 2, all these red colored districts can be found in Western Germany.
4) **Methodology**

4.1) **Network structures**

For answering the research question, different network models are developed to capture the flow of information from different providers to the individual farmer. Although, in the literature most networks only considering effects of farming neighbors or close non-business relationships, some more network structures are included in the analysis here, like the sales pattern of the manufacture, the dairy factory system and two kinds of extension service networks. As the dataset provides no information about social relationships of the farmers, various assumptions are made to build the different network structures. Furthermore, these networks have different network characteristic, but they all exhibit the same size with the 402 German districts as nodes.
In the following, the number of links, density (ratio: number of links in network to number of possible links), average degree (number of adjacent nodes), average shortest path (between two certain nodes) and the diameter (length of the largest path) are expressed for each network.

**Random network and neighborhood network**

In Figure 4 the random network graph and the neighborhood network as a spatial graph is shown. The first consists of randomly build links between the districts. With a diameter of 7 the paths in this network are a lot smaller than the neighborhood network.

*Figure 4: Random network and Neighborhood network*

<table>
<thead>
<tr>
<th>Random Network</th>
<th>Neighborhood Network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of links: 1053</td>
<td>Number of links: 1053</td>
</tr>
<tr>
<td>Density: 0.013</td>
<td>Density: 0.013</td>
</tr>
<tr>
<td>Average degree: 5.24</td>
<td>Average degree: 5.24</td>
</tr>
<tr>
<td>Average shortest path: 3.78</td>
<td>Average shortest path: 8.80</td>
</tr>
<tr>
<td>Diameter: 7</td>
<td>Diameter: 22</td>
</tr>
</tbody>
</table>

The traditional neighborhood network assumes that all farmers in one district know and relate to each other and the districts themselves are connected to their natural adjacent districts. Therefore, information and knowledge about AMS are flowing from each farmer in the network to the farmers in the same district, as assumed in the classical neighborhood effect models. Due to this assumption the average shortest path as well as the diameter is the largest of all considered networks.
Sales structure network and dairy factory network

Another network is depicted in Figure 5. As the dataset includes only installations of one manufacturer, the particular sales structure of this company can be a relevant driver in the diffusion of AMS. 20 sales centers spread all over Germany in 2013. Every sales center serves certain districts, whereby these sales regions do not match with the federal states and the size of each sales region vary. The network graph on the left size shows in its middle the different sales centers with their sales regions peripheral, respectively. Information provided by each sales center is spreading to the farmers in the respective served areas. Additional, it is assumed that the sales centers are connected, as they all belong to the same company, so that they can share their experiences and information among each other. The very small numbers of both, average shortest path and diameter is caused by ensuring this supply of close contact places for the farmers. The spatial network, on the right side, shows the same pattern displayed on the map of Germany.

*Figure 5: Sales structure network (network and spatial graph)*

<table>
<thead>
<tr>
<th>Sales Structure Network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of links: 573</td>
</tr>
<tr>
<td>Density: 0.0017</td>
</tr>
<tr>
<td>Average degree: 2.85</td>
</tr>
<tr>
<td>Average shortest path: 2.83</td>
</tr>
<tr>
<td>Diameter: 3</td>
</tr>
</tbody>
</table>

Another important partner of dairy farmers are processing centers. Some of them are divided into headquarters and branches. In total, the network includes 117 headquarters and 96 branches, as not all dairy factories have branches, but some have more than one (compare Figure 6). As can be
seen in the left network of Figure 6, some dairies have locations in different parts of Germany and operate nationwide. In the right network, the dairy factories are allowed to connect among themselves (here: links possible to the closest three dairy factories) for the exchange of information, which makes the network denser and shorter regarding the paths, while the number of links increases. For both networks is assumed that the farmers supply the closest dairy in distance, because there is no information available about the actual used dairy. If there is more than one in the same distance the factory is linked randomly. In addition, this network is built on the assumption, that the dairies are processing some material about innovations in the dairy sector to their suppliers, for example through flyers or information events.

Figure 6: Dairy factory network (with and without connections)

Consultation center network and organic farming association network

Extension service plays an important role in the diffusion of agricultural technology. In this study two different types are considered. The left side of Figure 7 presents a consultation center network of different central agricultural offices in Germany. These offices are responsible for
farmers in the respective federal state. Advice seeking farmers are assumed to contact the closest office to obtain information about new technologies and innovation.

The last network views organic farming associations, because AMS are promoted as appropriate for organic milk production (Sauer and Zilberman 2012), and mapped out on the right side of Figure 7. In total there are seven different associations in Germany: Biokreis, Bioland, Ecoland, Biopark, Demeter, Gää, Naturland. Some of them work only in certain districts, others are relevant nationwide and have also branches in different locations. Like before it is assumed that farmers, who are interested in organic production, join the closest organic farmer association, however, this is a very restrictive assumption, as organic production is often accompanied with a certain production philosophy, which can differ among the various associations.

Figure 7: Consultation center network and organic farming association network
4.2) Spatiotemporal epidemic model

Knox and Mantel test for spatiotemporal interaction

Before modelling the epidemic model, interaction in the dataset needs to be verified to assess evidence for spatiotemporal dependence (Held et al. 2005). It has to be tested in advance, if the cases of AMS installations tend to be close in time and space, or if other factors determine the pattern of installations. Classical approaches for testing interaction of a given point pattern \{ (s_i, t_i): i = 1, ..., n \} with spatial coordinates s_i and time points t_i observed in region W during a period (0,T], are the Mantel test and Knox test (Meyer et al. 2016b). Both measures are testing against the null hypothesis that the cases do not appear in spatiotemporal clusters and use a function of respective Euclidean distances to define space (d_s^{ij} = \|s_i - s_j\|) and time (d_t^{ij} = \|t_i - t_j\|) for a pair of events i and j (Meyer et al. 2016b).

The standardized Mantel test statistic as Pearson correlation (Mantel 1967; Meyer et al. 2016b):

\[
T_{Mantel} = \frac{1}{n(n-1)-2} \sum_{i=1}^{n} \sum_{j \neq i} \frac{d_t^{ij} - \bar{d}_t d_s^{ij} - \bar{d}_s}{\hat{\sigma}_d} ,
\]

with \( \bar{d} = \) sample means and \( \hat{\sigma}_d = \) standard deviations of the pairwise distances.

For the Knox test it is critical to predefine closeness in space and in time (Meyer et al. 2016b). In the case of AMS in Germany, close in time are installations done within one year (\( \tau = 365 \) days) or within half a year (\( \tau = 182 \) days), respectively. Close in distance are installations within the same district (\( \delta = 0 \)) or in adjacent districts (\( \delta = 1 \)), respectively. Knox test statistic (Knox and Bartlett 1964; Meyer et al. 2016b):

\[
T_{Knox} = \frac{1}{2} \sum_{i=1}^{n} \sum_{j \neq i} \mathbb{I}(d_s^{ij} \leq \delta) \mathbb{I}(d_t^{ij} \leq \tau),
\]

with \( \delta = \) closeness in space and \( \tau = \) closeness in time.

hhh4 model

In the case of diffusion of AMS in Germany the endemic-epidemic hhh4 model, developed by Held et al. (2005) is used. hhh4 is developed to analyze multivariate time series of counts, in particular infectious disease surveillance data. Due to various extensions (Held and Paul 2012; Paul et al. 2008; Paul and Held 2011; Paul and Meyer 2016; Meyer et al. 2016a, 2017) this model
can be applied to the diffusion and adoption of technology. The advantage of the model is the decomposition in an epidemic and endemic component, capturing different aspects of the diffusion process\(^1\).

In detail, the hhh4 model assumes that counts \(Y_{it}\) from unit \(i = 1, \ldots, I\) during periods \(t = 1, \ldots, T\) are negative binomial distributed with mean
\[
\mu_{it} = e_{it}v_{it} + \lambda_{it}Y_{i,t-1} + \phi_{it}\sum_{j \neq i} \omega_{ji}Y_{j,t-1},
\]  
(3)
conditional on past observations. Here, unit \(i\) equals the 402 German districts and period \(t\) of one year. As mentioned, the mean comprises of an endemic and an epidemic component. The parameter-driven endemic component \(v_{it}\) is estimated proportional to a region-specific and time-dependent offset \(e_{it}\). Usually the offset represents the population; here, it indicates the number of dairy cows in each district. The endemic component captures all factors determining the diffusion process which are not attributed to the previous number of cases. For a detailed description of endogenous factors, classical adoption determinants like the milk quota, the milk price or labor could be included as covariates. Additionally, it can display seasonal variations and trends. As in this case, diffusion of AMS technology is measured in terms of years, seasonality is excluded.

The other part of formula (3) shows the observation-driven epidemic component, which measures the influence of the past cases on the counts \(Y_{it}\) and allows in this way for temporal dependence beyond seasonality. It composes of the autoregressive effect \(\lambda_{it}Y_{i,t-1}\) and the spatiotemporal effect \(\phi_{it}\sum_{j \neq i} \omega_{ji}Y_{j,t-1}\). The first depicts the autoregression of adopted cases within the same district \(i\), the second captures the spatiotemporal influence of cases in another district \(j\). The weight \(\omega_{ji}\) specifies the diffusion flow of AMS and derives here from the previous introduced network structures.

The unknown parameters \(v_{it}, \lambda_{it}, \phi_{it}\) present log-linear predictors in the components. Their intercepts can be determined as unit-specific, random or identical across all units. Here, all districts are assumed to have identical intercepts of the unknown parameters in the estimation.

\(^1\) The description of the model follows Held et al. 2005; Paul and Held 2011; Meyer et al. 2016a
Evaluation of the model\(^2\)

As for each described network structure a hhh4 model is calculated, thus the different models need to be assessed to compare the fit of each network. The hhh4 model itself includes the measuring of the Akaike’s information criterion (AIC). Another way of comparing models of time series of counts is by estimating one-step-ahead forecasts with the observed data, followed by the usage of strictly proper scoring rules for evaluation.

In a first step, a one-step-ahead forecast is taken by estimating a predictive distribution \(P\) with mean \(\mu_P\) from the fitted hhh4 models. Afterwards the predictive quality of \(P\) is measured as a numerical score is assigned to the difference between the predictive distribution \(P\) and the observed value \(Y\) in the dataset. If the observed value \(Y\) is a realization from \(P\), the expected value becomes minimal and the scoring rule is proper. If the minimum of the value is unique, the scoring rule is said to be strictly proper. Commonly used proper scores for count data are the squared error score (SES), the logarithmic score (logS) and the ranked probability score (RPS). The scores are measured as follows:

\[
\text{SES}(P,y) = (y - \mu_P)^2, \tag{4}
\]
\[
\text{logS}(P,y) = -\log (P (Y = y)), \tag{5}
\]
\[
\text{RPS}(P,y) = \sum_{k=0}^{\infty} (P (Y \leq y) - 1(y \leq k))^2. \tag{6}
\]

While the SES is proper, because it depends only on the first moment of the predictive distribution \(P\), logS and RPS are strictly proper. Furthermore, logS is highly sensitive to extreme cases, in contrast to RPS.

Finally, according to the AIC, the model with the lowest score predicts the diffusion of AMS, via the respective network structure, best.

\(^2\) The description of the evaluation process follows Paul and Held 2011; Meyer et al. 2016a
5) **Results and discussion**

As explained in the previous section, first must be tested, if a spatiotemporal interaction can be assumed. Both, the Mantel- and the Knox-test reject the null hypothesis with a p-value = 0.563 for the Mantel-test and a p-value = 0.001 for all different Knox-tests (compare Table 1). This result suggests that there is an interaction of space and time in the dataset and the hhh4 models for the different network structures can be measured.

<table>
<thead>
<tr>
<th>Mantel-test</th>
<th>p = 0.563</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knox-test</td>
<td></td>
</tr>
<tr>
<td>( \tau = 182, \delta = 0 )</td>
<td>p = 0.001</td>
</tr>
<tr>
<td>( \tau = 182, \delta = 1 )</td>
<td>p = 0.001</td>
</tr>
<tr>
<td>( \tau = 365, \delta = 0 )</td>
<td>p = 0.001</td>
</tr>
<tr>
<td>( \tau = 365, \delta = 1 )</td>
<td>p = 0.001</td>
</tr>
</tbody>
</table>

*Table 1: p-values of Mantel-test and Knox-test*

The coefficients of the three estimated parameters in the hhh4 model are listed in Table 2, for each network structure. In summary, it can be said that the autoregression effect drives the annual diffusion of AMS in all models. The influence of the past observations in one district is the major effect. However, differences between the network structures emerge. While the random network faces the highest impact of the autoregression effect, the neighborhood network shows the lowest coefficient. In contrast, the neighborhood network exhibits the highest value of the spatiotemporal effect combined with the lowest influence of the endemic component. Overall, the endemic component has the lowest influence in the diffusion process through all considered networks in value. Despite the value, the share of the epidemic component\(^3\), which gives the proportion both epidemic effects are contributing to the model (Meyer et al. 2016a) is less than 50% for the dairy factory, the consultation center and the organic farming association network. With 70% has the sales structure network the highest share of the epidemic component.

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\(^3\) In Meyer et al, 2016a: named epidemic dominant eigenvalue (maxEV)
Regarding the evaluation of the hhh4 models estimated for the different network structures, the model with the lowest value measured by the proper scores, as well as the lowest value for the AIC, performs best (compare Table 3).

AIC, logS and RPS agree on the neighborhood network as the one with the best fit, what means that the neighborhood structure explains best the diffusion of AMS in Germany. This goes a long with a wide range of studies in literature. Furthermore, neighborhood effects are mainly considered while measuring the influence of networks on agricultural adoption. It seems like the advice and experience of farming neighbors are the most important ones in the decision making process of individual farmers. The neighborhood network is followed by the network describing
the sales structure of the manufacturer considered here. The sales structure is characterized by a comprehensive nationwide pattern. Therefore, the company offers large numbers of central contact points each farmer can turn to. This reduces the costs of information seeking before and during the technology adoption process. Interestingly, are both networks capturing the supply of extension services, performing worst. One could have expected that especially the network considering the consultation centers in Germany has a better explanatory power in the AMS diffusion process. The poor performance of the organic farming association network may be owed to the underlying assumptions. Due to no information about the share of organic farmers and the membership in one of the named organic farming associations, each farmer was assigned to the geographically closest association. This assignment may contradict to the philosophy going along with organic farming. The complete different order shown by the SES might be explained by the different measurement, as mentioned in the previous section.

6) Concluding remarks

This paper aims to analyze the spread of agricultural technology innovation through network structures and compares the influence of different kinds of network structures in the setting of automatic milking systems (AMS) in Germany between 1997 and 2013. The dataset provides information about the district and day of installed AMS in Germany, by one manufacturer. The number of AMS increases over time to its peak in 2012 with 575 installations. There are also differences in the adoption between different federal states noticeable.

Suggested by the literature, a spatiotemporal epidemic model is used to capture the dynamics of diffusion of technologies. Six different network structures are developed, assuming different characteristics and channels for information flow. These network structures are a random network, a neighborhood network, the sales structure network, a dairy factory network, a consultation center network and an organic farming association network.

The results show that the autoregression effect within one district determines the adoption of AMS in Germany. However, also the spatiotemporal effect has a noticeable influence on the diffusion of technology. This is the case, in particular, for the neighboring network. By contrast, the endemic component, capturing exogenous factors in the diffusion process, has the lowest impact in this case. In the presented estimation, no further factors are included in the model,
which can contribute to improve the understanding of diffusion and adoption of AMS. Additional variables might be e.g. the milk price, the milk quota, the amount of labor or the average herd size. All of those factors are identified to play an important role (Meskens et al. 2001; Sauer and Zilberman 2012). As variables are included as covariates in the endemic component of the model, it is expected that this component is gaining more explanatory power and a more complete picture of diffusion and adoption of AMS in Germany can be obtained. Furthermore, so far, the endemic component is kept constant over time. It is also feasible to allow for variance in it.

Regarding the evaluation of the performance of the networks, the neighborhood network fits best in the context of AMS diffusion. Information is flowing best from one farmer to another through the neighborhood structure network, which is confirmed by various studies. Nevertheless, the sales pattern of a commercial distribute technology can also play a huge role in the spread of technology. In this case, the company shows are comprehensive nationwide structure of sales centers. This can lead to a reduction in information seeking costs for the farmer. Although, promoted in the literature of adoption theory, extension services, represented by the consultation centers in each federal state of Germany, shows a poor performance in the explanation of adoption.

In a future work it is conceivable to improve the model through changing the assumption regarding the intercept of the single parameters. So far, all intercepts are identical across the districts. To capture the heterogeneity of the single districts the intercepts of the parameter might be assumed to be random or even district specific. Furthermore, the influence of the network characteristics on the final results needs to be detected. Not only the structure of each network is affecting the diffusion of technology, but also the characteristics of each network are determining its structure.
7) References


