Socio-spatial information sources influencing farmers' decision to use mechanical weeding in sugar beets

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Abstract

Farmers' decisions to adopt novel technologies are likely to be influenced by the behaviour of other farmers. Those effects are typically described as peer effects and are intensively studied. What remains unclear from the existing literature, however, is the general mechanism underlying those peer effects. Specifically, existing literature does not seem to clearly distinguish between 1) peer effects that result from information exchange, i.e. farmers talking to each other and 2) from the possibility of field observation, i.e. the possibility to observe the application of technology, the outcomes of the application, and the general state of the fields. We aim to study if information exchange and field observations are indeed two different mechanisms both leading to "peer effects". Therefore, we extend the existing theoretical assumptions on social learning and empirically explore the relationship between the two sources, hypothesizing that each provides complementary information due to the different underlying mechanisms. To study those two mechanisms, we focus on the example of mechanical weeding in sugar beets in Germany. We conduct an online survey among sugar beet farmers on the use of mechanical weeding in early 2022. Distinguishing between information exchange and field observation as two different mechanisms that drive peer effects, and understanding how they relate to each other, is crucial for designing effective extension services and policies to promote the adoption of desired farming practices.

Keywords Social network, spatial information diffusion, social learning, technology adoption, instrumental variables, mechanical weeding, farm survey

JEL code Q100 Agriculture: General, Q16 R&D; Agricultural Technology; Biofuels; Agricultural Extension Services, Q18 Agricultural Policy; Food Policy

Introduction

Promoting the adoption of new environmentally-benefitting technologies requires a full understanding of the drivers behind farmers' adoption decisions. Besides economic drivers, also behavioural factors play an important role in farmers' adoption decisions of new technologies such as sustainable farming practices (for an overview see Déssart, Barreiro-Hurlé, and van Bavel 2019).

This paper tackles the adoption decision by focusing on peer effects. More specifically, we investigate if the application of mechanical weeding in sugar beets in a farmers' socio-spatial environment affects adoption. The mechanism, we envisage is the diffusion of information through peers. Farmers rely on relevant, readily available, and low-cost information when deciding whether to adopt agricultural technologies (McBride and Daberkow 2003; Prokopy et al. 2019). Peer or neighbouring effects are assumed to be one important source of information that shapes farmers' decision-making (Foster and Rosenzweig 1995; Déssart, Barreiro-Hurlé, and van Bavel 2019; Skaalsveen, Ingram, and Urquhart 2020). The likelihood of adoption of new technologies varies depending on how many adopters are known (Bandiera and Rasul 2006; Conley and Udry 2010; Blasch et al. 2020). Additionally, there is theoretical and empirical evidence, that the likelihood of adoption of technology increases if the technology in use (Blasch et al. 2020), and especially its results can be observed easily (Rogers 2003; Llewellyn 2007; McCann et al. 2015).

Previous studies on peer effects, however, have not clearly distinguished between (verbal) information exchange between farmers on the one hand and the possibility to make field observations during the entire season in the neighbourhood on the other (e.g. Munshi 2004; Di Falco, Doku, and Mahajan 2020; Albizua et al. 2020). We hypothesize that these two information sources differ in the underlying mechanism and type of information delivered and thereby lead to the highest gain in information when both are present. Neglecting this difference might reduce the effectiveness of policies and extension services aiming to promote technology adoption. Including insights from behavioural economics, however, can help to design more effective policies (Streletskaya et al. 2020).

Therefore, we aim to determine how important information exchange and field observation are for farmers' adoption decisions by exploring the following questions:

1. How do information exchange and field observation in the same local setting influence adoption?
2. What is the size and structure of the network relevant from making field observations?

We aim to answer these questions in the case of mechanical weeding in German sugar beets. 2% of all German farms grew sugar beets on 9% of the total utilized agricultural area of Germany in 2020 (DESTATIS 2022). Current sugar beet farming in Germany depends mainly on herbicides for effective weed control. Regulatory approval of available active ingredients for herbicide applications are likely to get more limited due to environmental reasons, causing a need for alternative measures such as mechanical weeding (Warnecke-Busch, Mücke, and Others 2020; EU 2021). Mechanical weeding reveals clear ecological benefits such as increased biodiversity abundance compared to chemical weeding, but can also have negative effects such as soil erosion (Ulber et al. 2011; Deytieux et al. 2012; Liebman et al. 2016; Vasileiadis et al. 2017; Thiel, Mergenthaler, and Haberlah-Korr 2021). Thereby it might also exhibit a certain complexity, as costs (e.g. labour time) and effectiveness under different local conditions are difficult to predict (Gage and Schwartz-Lazaro 2019; Fishkis, Koch, and Others 2020). Based on Rogers' theory of diffusion of innovations (Rogers 2003), we conjecture that this complexity might be an adoption barrier. Information exchange and field observation of mechanically weeded fields could reduce complexity. Contrarily to Rogers' definition, we focus not only on the observability of results but also on whether the technology can be observed in use. While focusing on mechanical weeding our research can also shed light on how other technologies are diffused, for example, novel technologies such as mechanical weeding robots.

The remainder of the paper is structured as follows; first, a literature review is provided of previous research on peer effects in general and the role of defining the social network and its underlying mechanism in particular, then the methods including the development of our survey and sampling strategy are presented in detail before presenting and discussing the results. In the end, we conclude how our insights can be used for future policy design.

Literature review and theoretical framework

Factors influencing farmers' adoption decision of new technologies such as new sustainable farming practices have been studied increasingly over the last decades (for an overview see Déssart, Barreiro-Hurlé, and van Bavel 2019). A large number of existing studies in the broader literature has examined the role of different factors for the adoption of new technologies, such as precision farming (e.g. Kuehne et al. 2017; Vecchio, De Rosa, et al. 2020; Pagliacci et al. 2020; Ofori, Griffin, and Yeager 2020; Yatribi 2020; Tandogan and Gedikoglu 2020), or the decision to use mechanical alternatives to chemical weeding (Gent, De Wolf, and Pethybridge 2011; Melander et al. 2013; Damalas 2021).

Role of knowledge through peers

One important factor is knowledge and awareness. Prior theoretical and empirical research suggests that knowledge about new technology is positively related to its adoption (Kuehne et al. 2017; Prokopy et al. 2019; Vecchio, Agnusdei, et al. 2020). And lack of knowledge was identified as a major barrier to adoption (Foster and Rosenzweig 1995; Bakker et al. 2021). Previous studies have shown that farmers rely on relevant, local, readily available, and low-cost information when deciding whether to adopt agricultural technologies (McBride and Daberkow 2003; Šūmane et al. 2018; Prokopy et al. 2019).

To explain the mechanism through which knowledge increases adoption, we refer to Rogers' theory of diffusion of innovations (Rogers 2003). Rogers (2003) describes knowledge and awareness as the first stage in the diffusion of innovations. He further defines five perceived characteristics of an innovation that come into play in the second stage of "persuasion", including (3) the perceived complexity and (5) its observability. Knowledge about an innovation, for example through observing its results, can reduce its perceived complexity. Previous empirical studies have emphasized the role of perceived complexity as a barrier to adoption (Vecchio, Agnusdei, et al. 2020), and the possibility of its reduction if the effects of the innovation are easily observable (McCann et al. 2015). Reduced perceived complexity then leads to an increase in the likelihood of adoption of an innovation. Rogers (2003) states that knowledge is created through different sources of information at different stages in the adoption process. While Rogers's (2003) definition of "observability" describes the characteristic of an innovation, we further develop the term "field observation" as a mechanism underlying the effect of social learning. We explicitly refer to the possibility to observe **technology in use**, and not only its results.

A major source of information for farmers is extension services (McBride and Daberkow 2003; Llewellyn 2007; Wang, Lu, and Capareda 2020; Blasch et al. 2020; Wuepper, Roleff, and Finger 2021). But also, information from peers can be an important driver of adoption through social learning. Seminal contributions on the effect of social learning have been made (Timothy Besley and Case 1993; Foster and Rosenzweig 1995; Bandiera and Rasul 2006; Conley and Udry 2010; Krishnan and Patnam 2014). Munshi (2004) describes social learning as "[…] *a process by which an individual learns from his neighbours' experiences (their previous decisions and outcomes) about a new technology".* Following the earlier studies, also newer work found evidence of social learning. A recent qualitative study on no-till adoption in the UK by Skaalsveen (2020) concluded that so-called "intermediate farmers" are seen by other farmers as an important source of information as they have a high level of experiential knowledge. Lapierre et al. (2019) revealed that providing technical assistance to peer groups can be effective in significantly reducing pesticide use in France. Similarly, Sampson and Perry (2019) detect strong evidence of peer effects influencing farmers' decisions to adopt groundwater irrigation in the US. Läpple and Barham (2019) conducted a laboratory study on different sources of advice and found that participants take relatively more advice from peers than from experts. And Genius et al. (2014) discover peer effects and extension services to be both strong drivers of technology adoption and diffusion among olive farmers in Greece and that the two information channels reinforce each other's effectiveness.

These studies on social learning have chosen different ways to define the social network. Bandiera and Rasul (2006) distinguish between social networks based on self-reported individuals (e.g. T. G. Conley et al. 2003; Bandiera and Rasul 2006; Blasch et al. 2020; Albizua et al. 2020) versus those based on ex-ante set geographical and cultural proximity. Studies using the latter definition either refer to a certain radius (Foster and Rosenzweig 1995; Krishnan and Patnam 2014; Sampson and Perry 2019; Di Falco, Doku, and Mahajan 2020) or choose administrative districts like villages to define the social network (T. Besley and Case 1994; Munshi 2004).

Role of social norms

Peer effects might not only occur due to social learning but also due to social pressure based on social norms. In their overview, Déssart et al. (2019) distinguish between two types of social norms based on Cialdini et al. (1990): descriptive and injunctive norms. While the former describes the concern of what other people do (e.g. what I see in my social surrounding) the latter refers to norms that describe what people ought to do (e.g. what I think the others expect from me). There is evidence that both types of norms play a role in explaining farmers' adoption decisions of new sustainable farming practices and technologies (see overviews in Déssart et al. (2019), Tandogan and Gedikoglu (2020) and Streletskaya et al. (2020)).

We assume that social norms, in our case especially descriptive norms, can be a driver of peer effects. On the one hand, talking to other farmers could lead to social pressure, a farmer gets to know what the others do (descriptive norms) or feels expectations from the others (injunctive norms). On the other hand, social pressure could also arise when a farmer is seen on the field while spraying (observability of technology in use), or when the outcome of herbicide application is visible on the field (observability of effects of technology). Hence social norms could work either through information exchange or field observation. In both cases, the wish to conform with norms could influence farmers' adoption decisions.

Mechanism underlying social learning

However, evidence on the underlying mechanism leading to social learning through the social network remains inconclusive. Previous research assumes that knowing adopters and verbally exchanging information with them leads to social learning through the same mechanism as observing adopters' in action or their fields (Figure 1).

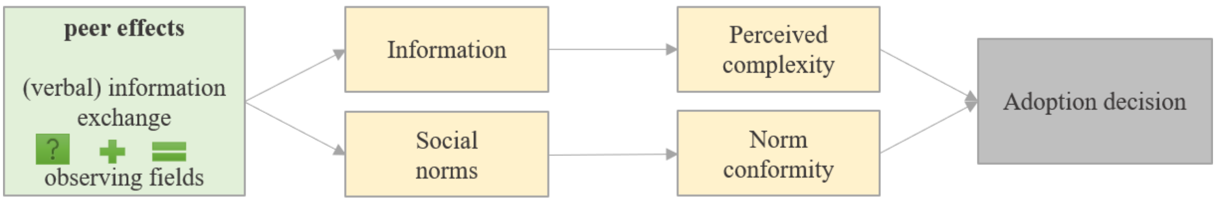

Figure 1: Mechanism behind social learning

While Albizua et al. (2020) explain social learning through purely verbal exchange with peers, Munshi (2004) and Di Falco et al. (2020) imply field observation by spatial proximity. Similarly, Bandiera and Rasul (2006) and Blasch et al. (2020) imply field observations through knowing other adopters. Some studies suppose a mix of both as in Conley and Udry (2001; 2010) or Krishnan and Patnam (2014) who suggest social learning occurs " *[…]by talking to friends or neighbours, or, to a lesser extent, by observing early adopters*". Sampson and Perry (2019) found that one additional neighbour, whereby neighbour is defined by spatial distance, adopting groundwater for irrigation increases groundwater adoption. The average marginal effect of one additional peer is reduced by distance and diminishes as the total number of neighbours adopting groundwater increases. But the underlying effect is simply called "learning". In all these cases it is not distinguished and discussed what drives the peer effect, is it knowing adopters or observing their fields or a combination of both?

Therefore, in this paper we aim to detangle the effect of verbal information exchange and observing fields, so far lacking in the scientific literature. We assume that (verbal) *information exchange* and *field observation,* in the same local setting over a full production period, have to be distinguished as two different mechanisms, that deliver different information and are both observed as social learning (Figure 1).

We assume that through observing an innovation in use in the same local setting, such as soil type, climate, or topography, farmers receive relevant, low-cost, easily available information. We base this assumption on evidence from Lewellyn (2007) and Šūmane et al. (2018), who found that especially local information is of major relevance to farmers as seeking and learning costs are reduced. This is supported by evidence from Läpple et al. (2017) and Vroege et al. (2020) which both find that farmers in close spatial proximity exhibit similar patterns in decision making and from Assunção et al. (2019) who detect spatial heterogeneity to reduce adoption rates of new technology. Additionally, observing an innovation over a long time, for crops for example over a whole production period, allows observing the technologies' feasibility and results. This relevant information might reduce the perceived complexity and thereby increase the likelihood of its adoption.

On the other hand, talking to peers delivers information that can reduce perceived complexity, too. Peers can be neighbours in close spatial proximity, but also other farmers met at fairs and field days or other people whose opinion is important, such as relatives. In contrast to information from observing fields, which mainly undergoes the interpretation of the observer, information from the verbal exchange is prone to bias from two sides, as those who give information and those who receive it might add some interpretation. While observing fields might reduce perceived complexity through information on feasibility and results, the verbal exchange might deliver information on costs and benefits that cannot be observed directly.

For both information sources, the relevance of certain farmers or fields might differ. A convinced conventional farmer might not consider what a convinced organic farmer does on her fields or tells. Not all people in a social network are considered as relevant peers, e.g. not all farmers in a village are important for a farmer's decision making. There is evidence that only a certain number of adopters known positively affects their own adoption decision (Conley and Udry 2010; Blasch et al. 2020) and that too many adopters in a social network can even decrease the likelihood of adoption of new technology (Bandiera and Rasul 2006; Sampson and Perry 2019).

Contrary to these existing studies that use ex-ante set spatial proximity to define the social network (e.g. T. Besley and Case 1994; Foster and Rosenzweig 1995; Munshi 2004; Krishnan and Patnam 2014; Sampson and Perry 2019; Di Falco, Doku, and Mahajan 2020), we exploratively ask for the fields that are observed to then define the size (number of fields and farmers involved) and structure (spatial distance) of the social network.

Hypotheses

Based on the existing literature we formulate our first hypotheses as follows: We expect that those farmers who are aware of at least one other farmer doing mechanical weeding in their surroundings show a larger likelihood of using mechanical weeding themselves and that with an increasing number of farmers being aware of doing mechanical weeding the likelihood increases. The information mechanism behind relies on the verbal exchange between farmers about their experiences and could also include peer pressure through injunctive or descriptive norms (H1a).

Similarly, we assume that those farmers who are aware of at least one other field where mechanical weeding is done in their surroundings show a larger likelihood of using mechanical weeding themselves and that with an increasing number of fields in close spatial proximity being aware of where mechanical weeding is done the likelihood increases. In this case relevant, low-cost information and (descriptive) norms are obtained from observing fields over a long period in spatial proximity e.g. same conditions as own fields (H1b).

Method and data

Survey and Sampling strategy

To exploratively investigate the importance of information exchange and field observation, we conduct an online survey among German sugar beet farmers in early 2022. The survey is still ongoing and we present preliminary result based on a sample of the first 60 participants (Status 18.03.2022).

Survey

The survey is preregistered and the empirical study plan is outlined using the open science framework (OSF) platform (Massfeller and Storm 2022). In this survey, farmers are asked to specify which mechanical weeding techniques they use (concrete machinery, ownership status) and when they started to use these machines. Next, participants have to indicate if they are aware of other farmers that use mechanical weeding. Farmers are then asked to state on an interactive map where they grow sugar beets and if they can indicate fields of other farmers using mechanical weeding (in sugar beet or other crops). For those who don't use mechanical weeding, we ask for reasons not to do so. All participants are asked about their intention to use new weeding technologies in the upcoming years.

Technical design and implementation

We designed and implemented a custom build survey tool that allows us to obtain explicit spatial data. Therefore, we used free available geo-data on field shapes for some federal states of Germany as well as remote sensing data from Copernicus for the remaining federal states. Thereby participants can select their own but also others' fields either by clicking on fields or by setting a marker (tractor symbol) (Figure 2).

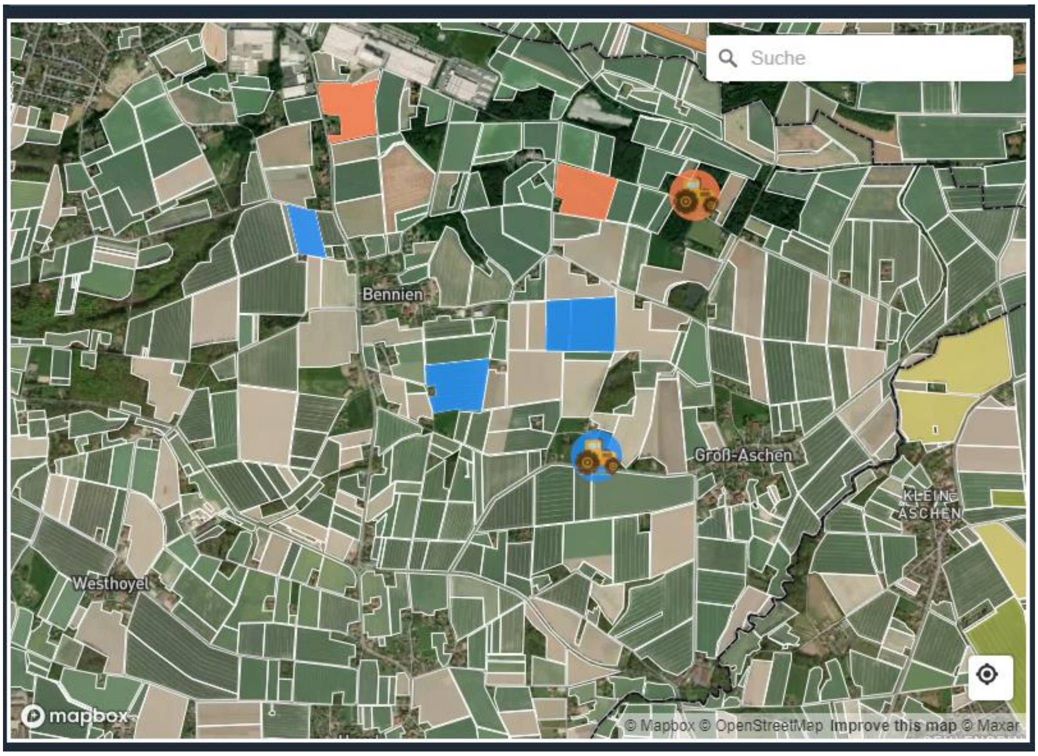

Figure 2: Survey tool, orange indicates own fields, blue indicates other farmers' fields where mechanical weeding was observed

Sampling strategy

We rely on a convenience sample as we publish advertisements off- and online as well as making use of the advisory network of the German sugar beet industry and the institute for sugar beet research (IFZ). As pointed out by Lowenberg-DeBoer and Erickson (2019), transparent sampling procedures and representative samples are key to drawing meaningful conclusions in the field of agricultural technology adoption. Convenience samples can be prone to bias, such as reaching mostly people that are already interested in the topic. Especially online surveys might be answered by farmers younger and better educated than the average farmer in Germany. However, we assume that it is unlikely that those biases will substantially influence our results. In our survey, we focus on two main aspects: How many other farmers are known that do mechanical weeding and on which fields mechanical weeding is observed. We expect, that these two aspects are not influenced by an interest in the topic. We are primarily interested to explore how observing fields and knowing other farmers might influence adoption, but not in technique and adoption rate itself. To consider all possible consequences of a biased sample we assume the "worst case": a sample consisting of farmers much younger, much better educated, much more open, and interested in the topic of mechanical weeding than the average sugar beet farmers in Germany. There is evidence, that farmers who are better informed and educated do not rely as much on what their peers do compared to those less informed (Bandiera and Rasul 2006). From this, the problem could occur, that we underestimate the effect of knowing other farmers and of observing fields. Nevertheless, we would still be able to say something about the relation between these two information sources. Hence, we interpret our results carefully and if our sample is indeed younger than the population on average we consider this in the interpretation wherein the worst case our effects underestimate the true effect. Based on a power analysis[1], we aim for a sample size of between 180 and 500 observations (more details can be found in the pre-registration file (Massfeller and Storm 2022)).

Models

To answer our first research question "How do information exchange and field observation in the same local setting influence adoption?" we aim to test two hypothesis. First, we hypothesis that the number of other adopters known (H1a) and second that the number of mechanically weeded fields observed (H1b) both increase the likelihood of adoption. To test those hypotheses, we run a binary model explaining adoption of mechanical weeding as the dependent variable ($Adopt_i$). Information about the number of other adopters is used to approximate the possibility of *information exchange* and enters our model as $Info_i$, while the number of mechanically weeded fields from others provides information about the awareness of other fields and the possibilities to make *field observations,* is denoted $Field_i$. In addition, we include a vector of control variables $Control_i$ such as farmers' age, farm size, and previous participation in Agri-environmental schemes (AES).

We denote farmer *i*'s indication to adopt mechanical weeding by $Adopt_i$, which is modelled as a binary decision-taking 0 or 1. We followed a probit specification and a farmer's probability to adopt mechanical weeding is modelled as follows:

$$\Pr(Adopt_i=1|Info_i,\ Field_i, Control_i, \beta, \boldsymbol{\gamma}) = \Phi(\beta_0 + \beta_1 Info_i + \beta_2 Field_i + \boldsymbol{\gamma} Control_i + \varepsilon_i)$$

[1] All calculations were carried out with the power analysis tool G*Power (Faul et al. 2007, 2009)

wherein Φ denotes the normal cumulative distribution function, the β's denote scalars and $\boldsymbol{\gamma}$ a vector of coefficients to be estimated. We estimated the model in (1) using maximum likelihood.

Descriptive Statistics

Our preliminary sample consists of 60 farmers, mainly specialized in crop production (69%). Compared to the German farming census from 2020 (see Table 1), participants in our sample are slightly younger than the German average, a common observation in online surveys. Farms are slightly larger than the German average. Concerning the share of organic farms and the share of farms participating in a voluntary agri-environmental scheme (AES, pillar 2 measure), our sample is in the same range as the German farming census.

Table 1: Sample statistics and comparison to German farm census data from 2020

	Whole sample (n = 60)	Farming census in Germany[a]
Variable	Mode	Mode
Age in years	35 – 44	55 - 64
Farm size (in ha)	50 – 99	20 – 50
Share of farms currently having implemented AES	79 %	85 %[b]
Share of organic farms	6 %	9 %

[a](Bundesministerium für Ernährung und Landwirtschaft 2021b)
[b](Bundesministerium für Ernährung und Landwirtschaft 2021a)

Out of 60 participants, 17 (28 %) use mechanical weeding in their sugar beet production. Figure 3 shows which machines these adopters use and when they have been adopted.

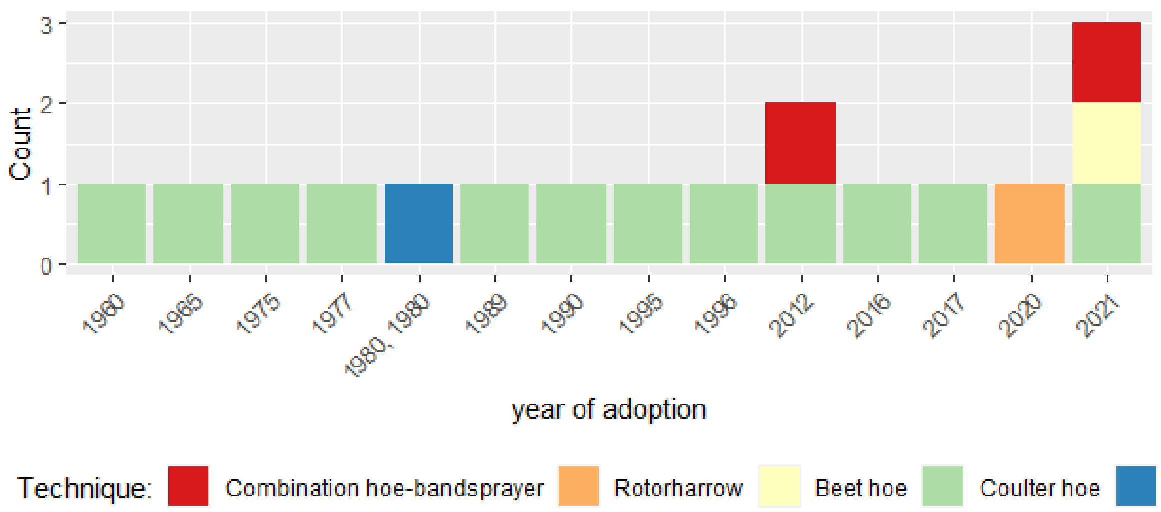

Figure 3: Mechanical weeding techniques in use over time

Figures 4 -6 show the distribution of answers concerning the size and structure of the social network. Most farmers know 1 - 5 adopters (Figure 4) and are aware of 1 - 5 fields on which weeds are mechanically weeded (Figure 5). For most farmers, these fields are 0 -5 km away (Figure 6).

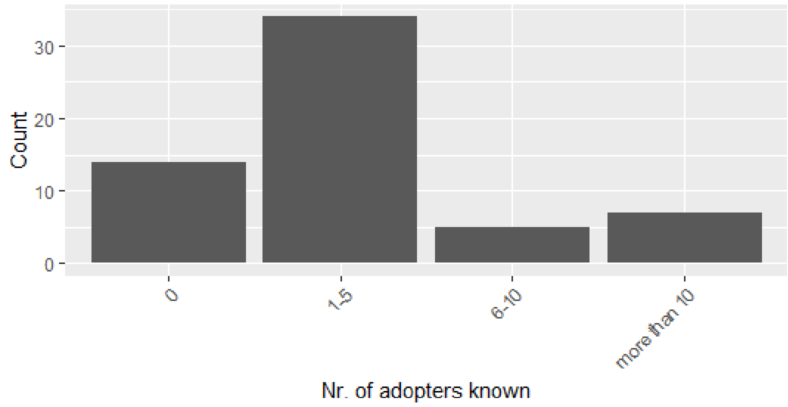

Figure 4: Adopters of mechanical weeding known

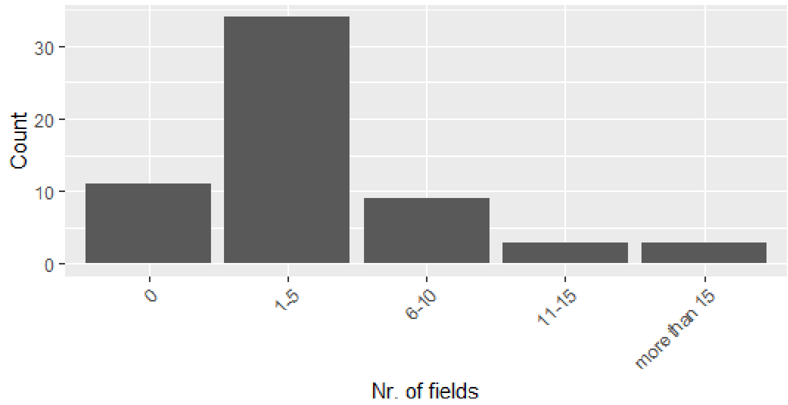

Figure 5: Fields aware of on which mechanical weeding is done

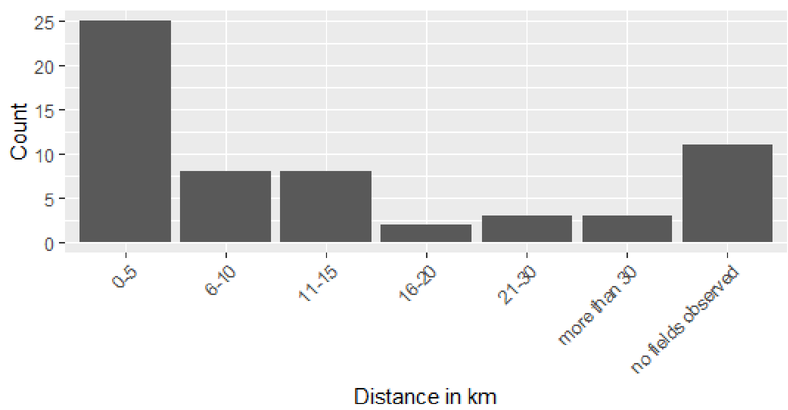

Figure 6: Distance to fields on which mechanical weeding is done

Results

Given the small preliminary sample size, we opted for a more parsimonious model compared to the preregistration including only our two variables of interest, *Info*$_{i,}$ and *Field*$_i$ as well as the three Control variables as binary dummies (farmers' age > 45 years, farm size > 50 ha, and AES-participation in the current funding period). Figure 7 displays acoefficient plot of the results. For both variables, *Info*$_i$ and *Field*$_i$, the reference group is that of no adopters known and no fields observed, respectively.

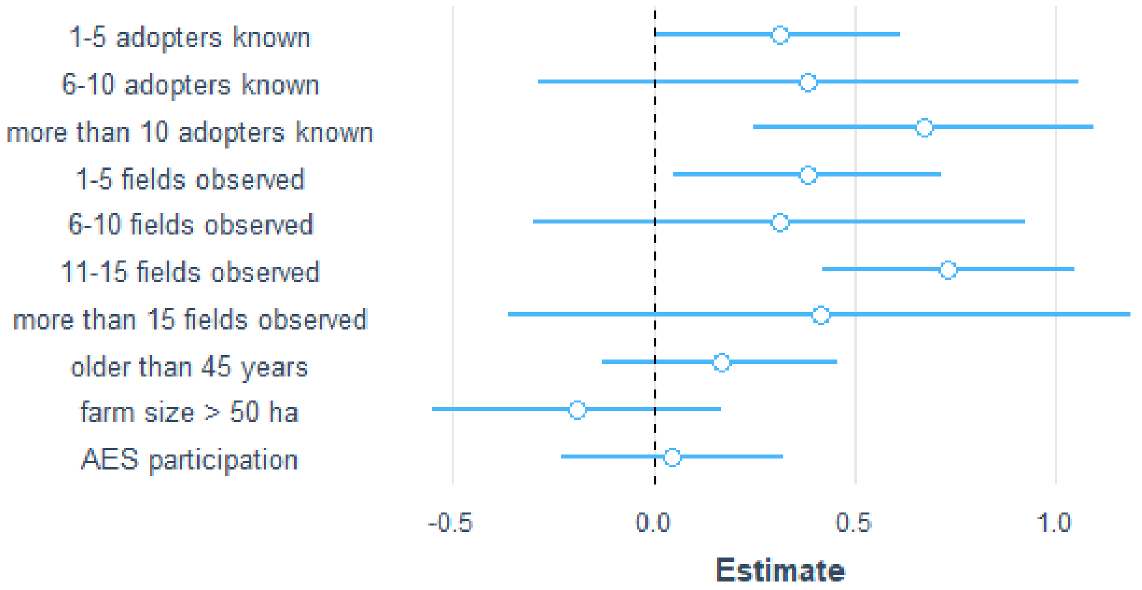

Figure 7: Dependent variable: Adoption, Observations: 59, Displaying confidence interval of 0.95

We find that those who know 1-5 adopters have a statistically significant larger likelihood of having adopted mechanical weeding, compared to those who know no adopters. The effect size of 0.311 indicates that knowing 1-5 adopters increases the likelihood by 31%, compared to those who know no adopters. Similarly, those who know more than ten adopters exhibit a statistically significant larger likelihood of having adopted mechanical weeding. The average effect of 0.672 indicates that knowing ten or more adopters increases the likelihood by 67%, compared to those who know no adopters.

Concerning the number of fields observed, those who observe 1-5 fields show a statistically significant larger likelihood of having adopted mechanical weeding (marginal effect of 38%), similarly having observed 11-15 fields increases the likelihood of adoption statistically significantly by 73%. Concerning the control variables, we find a positive relationship between age and likelihood of adoption and AES participation and likelihood of adoption, the farm size is negatively related to the likelihood of adoption.

We asked the farmers for their intention to use different technologies of mechanical weeding in the next 5 years (Figure 8). We thereby differentiated between traditional mechanical weeding (e.g. tractor-mounted hoes and harrows), modern mechanical weeding (tractor-mounted and camera-steered or GPS-supported), and autonomous mechanical weeding (e.g. robots).

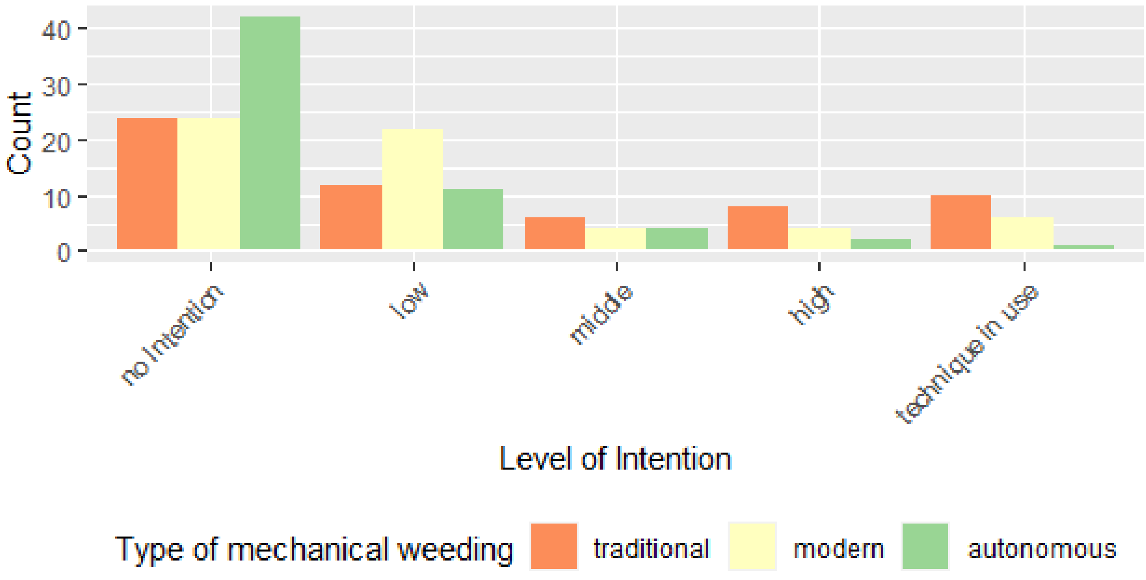

Figure 8: Intention to use different types of mechanical weeding in the future

It can be seen that most farmers do not intend to use any type of mechanical weeding in the future. Their intention is low, especially for traditional and autonomous technologies. Those who intend to adopt in the future (middle and high intention) prefer traditional techniques. Adopters mainly use traditional and modern techniques.

We asked the non-adopters for the reason not to use mechanical weeding (Figure 9). The three main reasons are perceived time constraints, perceived low reliability of the technique to remove all weeds efficiently, and high investment costs.

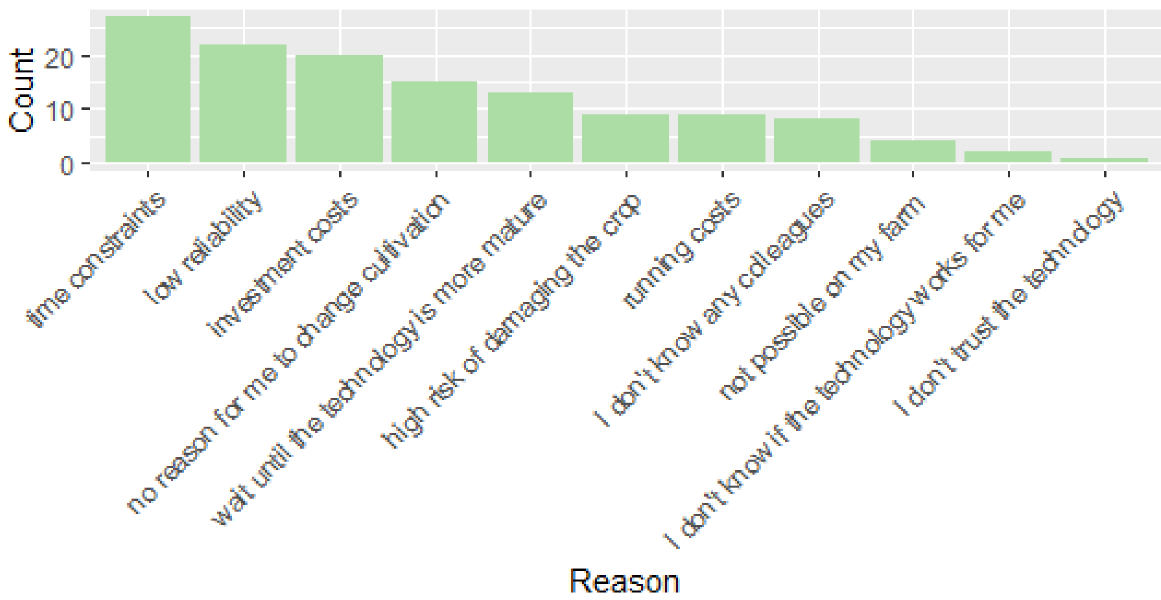

Figure 9: Reasons for non-adoption of mechanical weeding

Discussion

Our preliminary results provide first insights to answer our research question 1 of how to do information exchange and field observation in the same local setting influence adoption. The results support our initial hypotheses: Those farmers who are aware of at least one other farmer doing mechanical weeding in their surroundings show a larger likelihood of using mechanical weeding themselves and with an increasing number of farmers being aware of doing mechanical weeding the likelihood increases (H1a) and those farmers who are aware of at least one other field where mechanical weeding is done in their surrounding show a larger likelihood of using mechanical weeding themselves and with an increasing number of fields observed the likelihood increases (H1b). The two variables $Info_i$ and $Field_i$ are both positively related to the adoption decision while controlling for farms size, age of the farmer, and current participation in AES. Knowing 1- 5 adopters increases the likelihood of adoption by 31 %, but knowing more than 10 farmers even by 67%, compared to those who don't know any adopters. Similarly observing 1 -5 fields increases the likelihood of adoption by around 38%, observing 11 – 15 fields even by 73%. It seems that both mechanisms, *information exchange,* and *field observation*, both lead to an increase in the adoption of mechanical weeding, assumedly by delivering relevant information and/or by activating social norms.

Concerning our second research question of what is the size and structure of the network relevant from making field observations, we found that most farmers observe rather only a few fields (1-5) in their close spatial surroundings (1-5 km). This could support our assumption, that especially local information from farmers and fields that face the same local settings are relevant. Most farmers know 1-5 adopters, so here too, the social network seems rather small. However, knowing more adopters and observing more fields seems to increases the likelihood of participation even more.

Having in mind the low intention among participants to use different types of mechanical weeding in the upcoming years, we conclude, that policies should focus on fostering this intention. We found, that the main reasons for non-adoption relate to perceived costs in terms of time, money and possible yield decreases due to insufficient weed removal. This information is valuable information for tech developers which primarily need to ensure that mechanical weeding technologies remove weeds efficiently and reliably in different conditions. Time constraints could relate to the time to do the mechanical weeding, but for future technologies such as robots also supervision time could be a barrier and should be minimized.

After completion of the survey, we plan to extend our approach by including spatially explicit variables, such as the distance to the fields observed, distance to demonstration farms, and belonging to advisory regions. We plan to apply an instrumental variable approach to deal with the problem of endogeneity that might be induced by the other farmers' adoption decisions. Lastly, we plan to examine the relation between the two information sources, particularly if $Info_i$ and $Field_i$ complement or substitute each other? Therefore, we want to look at the joint and individual contributions in models including either only of the variables or both.

One limitation of our identification strategy is that we cannot account for the temporal order of adoption. We might be able to detect spatial patterns and a correlation between own adoption and other farmers' behaviour, but we don't know who followed whom in adopting. One option to partly account for that is the extension of the model by a variable capturing the "status quo" of mechanical weeding in a certain area at the point of adoption. Depending on data availability we might be able to control for this "status quo" of adoption of mechanical weeding in a certain spatial area (postal code, advisory region) as we ask in our survey for the year of first use of a certain technique ($Tech_i$). Thereby we can get insights on the temporal order of adoption: Who was an early adopter? Who followed whom in adopting? However, that would required substantial coverage of farm in a region, which might be difficult to obtain.

Conclusion

We expanded the existing knowledge on peer effects by separating between two different mechanisms, namely *information exchange* and *field observations,* that can lead to peer effects. We developed an extension of the existing theory explaining peer effects and social learning. We studied the empirical importance of those mechanisms using a novel survey tool developed for this purpose. The obtained results provide useful information for designing more effective extension services and policies. Additionally, results could be used to inform tech developers about current perceived barriers of adoption and how to tackle them by designing technologies aligned to farmers' needs. We found that *field observations* as well as *information exchange* contribute to explain the adoption decision to use mechanical weeding in German sugar beets. Our data revealed that the intention to use different types of mechanical weeding in the upcoming years is very low, especially concerning modern and autonomous technologies. We identified key barriers for adoption, namely time constraints, investment costs, and unreliability.

Based on these first, preliminary results, we draw four conclusions. First, the main task for policies is to foster the intention to use mechanical weeding in the future. Second, as we found that field observation matters, this could be done by supporting farmers, for example, by allowing them to try a new technology for a year at a low price, or by cooperating with farmers to establish demonstration farms that test new technologies over a longer period. Third, as information exchange between farmers matters, too, also measures such as discussion rounds and best-practice exchanges could prove efficient to foster adoption and intention. And fourth, the barriers to adoption we identified should be taken up by policymakers but also by tech developers. Future mechanical weeding technologies should be designed in a way, that doesn't require much (supervision) time and they should remove weeds efficiently and reliably at a low cost.

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