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ORIGINAL ARTICLE

Field observation and verbal exchange as different peer effects in farmers' technology adoption decisions

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Abstract

Farmers' adoption of novel technologies is influenced by other farmers' behavior, a phenomenon known as peer effects. Although such effects have been studied intensively, the literature does not clearly distinguish between those that result (1) from verbal exchanges with other farmers and (2) from field observations, including the application of technology, its outcomes, and field conditions. We extend existing theoretical concepts and hypothesize that verbal information exchanges and field observations are two types of peer effects. Using data from an online survey of German sugar beet farmers' application of mechanical weeding from early 2022, we find that the likelihood of adopting mechanical weeding increases across all model specifications by around 26%–28% if at least one adopter is known and by approximately 30%–32% if at least one field is observed. The two types of peer effects complement and reinforce each other in explaining adoption decisions. The effects increase with the number of adopters known and fields observed but decrease with larger distances to the observed fields. The findings can support designing extension services and future peer effects research that should consider the distinction between peer effects arising from verbal exchanges and field observations.

KEYWORDS

peer effects, social network, spatial information diffusion, technology adoption

JEL CLASSIFICATION

Q16, Q18, Q100

1 | INTRODUCTION

Peer behavior is an essential driver of farmers' technology adoption decisions (Shang et al., 2021). Exchange with peers could increase farmers' intention to adopt novel sustainable farming practices (Sampson & Perry, 2019), to reduce pesticide usage (Bakker et al., 2021), and can

reinforce the effectiveness of advisory services (Genius et al., 2014). The rich body of literature on the role of peers considers various ways to define “peer effects” covering purely verbal exchange with adopters (Albizua et al., 2020) and field observation (Mekonnen et al., 2022). However, existing studies do not consider to what extent these types of peer effects differ. Deeper knowledge of

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the mechanism that underlies peer effects is important for improving advisory services and policy measures, but missing (Bartkowski & Bartke, 2018; Bramoullé et al., 2020; Brown et al., 2018; Pe'er et al., 2020). So far, the variety of definitions in the current literature makes it difficult to understand the mechanism underlying peer effects: is it through verbal exchange, field observation, or a mix of both?

The research objective of this paper is to disentangle (*verbal*) *information exchange with adopters from observing fields on which a (new) technology is or was used* as two distinct types of peer effects. We are interested in the correlation between the two potential types of peer effects, verbal exchange and field observation, and farmers' technology adoption decisions. Further, we aim to understand how the two types relate to each other. Ideally, we would be able to identify causal effect of verbal exchange and field observations on adoption. However, as outlined in detail below, doing so is conceptually challenging. Nevertheless, studying the correlation between the two types of peer effects (verbal exchange and field observation) and their relation to adoption allows us to derive information on their relative importance and difference. To reach our objectives, we structure our analysis along the following research questions:

1. How do (verbal) information exchange and field observation relate to adoption of technology?
2. Do the two types complement each other in explaining the technology adoption decision?
3. How do the two types relate to each other within the relevant socio-spatial network¹?

We focus on farmers' decision to use mechanical weeding using data from an online survey with sugar beet farmers from early 2022. The German sugar beet production sector is characterized by well-organized advisory structures that deliver information through sugar beet factories, sugar beet associations, and sugar producers to farmers. Current German sugar beet farming depends mainly on herbicides for effective weed control. Herbicide usage is among the main drivers of biodiversity loss in agricultural areas in the European Union (EU) (Gill & Garg, 2014; Petit et al., 2015). The regulatory approval of available active ingredients for herbicide applications is likely to become more limited due to environmental concerns, leading to the need for alternative measures, such as mechanical weeding (EU, 2012; Warnecke-Busch et al., 2020). Novel technologies, such as weeding robots,

allow farmers to reduce herbicide usage while maintaining high yields, thereby decreasing agricultural production's negative impacts on biodiversity (Finger et al., 2019). Mechanical weeding has clear ecological benefits, including increased biodiversity abundance compared to chemical weeding, but it can also have adverse effects, such as soil erosion (Liebman et al., 2016; Thiel et al., 2021; Ulber et al., 2011; Vasileiadis et al., 2017).

The relations between individual's outcomes and those of their peers, known as "peer effects" (Bramoullé et al., 2009), have received intensive study in the domain of farmers' technology adoption decisions in different geographical and cultural contexts. Bandiera and Rasul (2006) distinguish between social networks based on self-reported individuals versus those based on ex-ante set geographical and cultural proximity. The former are defined as peer effects, either based on purely verbal information exchange (Albizua et al., 2020), take into account whether the adopters are known (Bandiera & Rasul, 2006; Blasch et al., 2020), or focus on the awareness of other farmers and their fields (Conley & Udry, 2001, 2010; Conley et al., 2003; Mekonnen et al., 2022) to approach field observation. The latter presumes a (more or less clearly defined) mix of verbal and visual information, implicating field observation through spatial proximity. Some empirical studies refer to a certain radius (Di Falco et al., 2020; Kolady et al., 2021; Krishnan & Patnam, 2014; Läpple et al., 2017; Sampson & Perry, 2019) and others to administrative districts, such as villages (Besley & Case, 1993; Foster & Rosenzweig, 1995; Munshi, 2004). However, insight into the mechanism underlying peer effects is limited (Bramoullé et al., 2020), and statistical evidence for the role of farmer-to-farmer interaction in farmers' technology adoption decisions is scarce (Shang et al., 2021). So far as we know, no previous research has explicitly investigated the differences between verbal exchange and field observation as two distinct types of peer effects. We intend to derive a first indication of the importance of and difference between the two types of peer effects that can serve as the basis for future research in this direction.

We find that verbal exchange and field observation both positively relate to the adoption decision, whereby verbal information exchange seems to be relatively slightly more important than field observation in predicting adoption. Hence, personally knowing adopters and verbally exchanging information regarding mechanical weeding might play an important role for the adoption decision, besides observing mechanical weeding on other farmers' fields. Despite the high correlation between the two types of peer effects, we are able to estimate separate effects indicating complementarity in explaining the adoption decision. We show that in a relevant socio-spatial network, which is large in terms of number of known adopters and

¹We define the term "socio-spatial network" as the composition of the number of adopters known, the number of fields observed and the distance to the fields observed.

number of fields observed but is small in terms of spatial radius, verbal exchange and field observation reinforce each other.

With this study, we improve the understanding of the mechanism underlying peer effects by being the first to clearly differentiate between (verbal) information exchange and field observation as distinct types of peer effects. Our empirical investigation contributes to examining the extent to which the two types relate to the adoption decision and how far they complement and reinforce each other. Based on our findings, future research can further explore the mechanism and causal relationships behind these two types of peer effects. Additionally, we present a novel survey tool that allows us to capture spatially explicit data on farmers' own fields and the fields they observe, which might also help answer other research questions. Lastly, our findings allow us to derive implications for designing advisory services and policies aiming at reduced herbicide usage or technology adoption. We derive that combining opportunities for verbal exchange with the option to observe a technology and its results in use might prove most efficient in steering farmers' behavior in a desired direction. While we focus on mechanical weeding, our research can also show how other novel technologies are diffused, such as mechanical weeding robots.

The remainder of our paper is structured as follows. We first derive our hypotheses based on existing literature on peer effects in Section 2. In Section 3, we describe in detail the development of our survey and explain the methods used, including our empirical strategy of how to deal with Manski's reflection problem (Manski, 1993) in peer effects. We then present and discuss our findings in Section 4 and conclude with implications for future research and policy design in Section 5.

2 | PEER EFFECTS IN TECHNOLOGY ADOPTION AND DERIVATION OF HYPOTHESES

In his theory of diffusion of innovations, Rogers (2003) describes the necessary knowledge of an innovation as created through different sources of information at different stages in the adoption process. Peers are a critical source of information, as they provide relevant, readily available, and low-cost information (McBride & Daberkow, 2003; Noy & Jabbour, 2020; Prokopy et al., 2019; Šūmane et al., 2018) and thereby shape farmers' decision making (Foster & Rosenzweig, 1995; Skaalsveen et al., 2020; Villamayor-Tomas et al., 2021). The relevance of this information could differ depending on who is considered important, such as family members, friends, or other successful farmers (Bessette, Zwickle, & Wilson, 2019; Genius et al., 2014;

Mekonnen et al., 2022), if the other is well known (Mansson et al., 2016) or has deep roots in the community (Noy & Jabbour, 2020).

2.1 | Verbal exchange with adopters

Face-to-face interactions with peers are among farmers' most important sources of information (Skaalsveen et al., 2020). Talking to peers can happen with intent but could also be prone to some bias, either in terms of whom one chooses to speak with (Krishnan & Patnam, 2014) or in terms of the interpretation that the speaker or listener might add (Mekonnen et al., 2022). Through verbal exchange, information about unobservable characteristics of a technology, like costs, expected herbicide reductions, time and labor requirements, or necessary skills, can be obtained (Albizua et al., 2020; Jabbour et al., 2014). Studies of peer effects based on verbal exchange often include the frequency of communication (Conley et al., 2003; Tran-Nam & Tiet, 2022), account for the number of adopters known and the distance to them (Krishnan & Patnam, 2014; Sampson & Perry, 2019), or differentiate between different types of peers talked to (Albizua et al., 2020; Mekonnen et al., 2022). We assume that for verbal exchange, peers can be neighbors in close spatial proximity, as well as other farmers who were met at fairs and on field days and whose opinions are important but who are not nearby.

2.2 | Observation of adopters' fields

Rogers (2003) describes observability as an important characteristic of an innovation. We broaden this definition by explicitly referring to the possibility of observing a technology in use, not only its results. Fields could be observed rather unconsciously, as a farmer might observe a field when passing but without actively thinking of it (McCann et al., 2015) or as a conscious action known as "road-side farming" (Burton, 2004), describing the process of farmers checking out "symbols of good farming" on neighboring farms and fields. In the case of weed management, these symbols can be easily observed, for example, in terms of tidy, weed-free fields or high yields (Lavoie & Wardropper, 2021). There is empirical evidence that the likelihood of adoption varies depending on whether the technology is in use (Blasch et al., 2020), and especially if its results can be observed easily (Llewellyn, 2007; McCann et al., 2015). Moreover, local information has been found to be of major importance, as farmers close by might face the same production conditions (Arbuckle et al., 2013; Llewellyn, 2007; Noy & Jabbour, 2020; Šūmane et al., 2018). Mekonnen

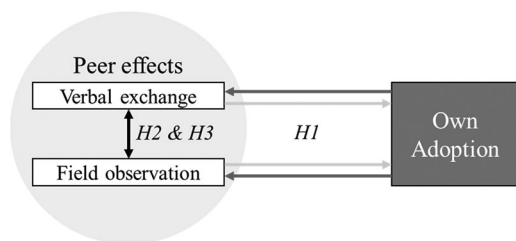


FIGURE 1 Types of peer effects.

Source: Own presentation.

et al. (2022) found that spatial proximity and knowledge of peers' decisions on the use of agricultural inputs and their outcomes, combined with awareness of their plots, explain information diffusion through peers. However, little statistical evidence on the importance of observability as a relevant attribute of technologies for the adoption and diffusion of digital farming technologies has been published (Shang et al., 2021). We assume that observing the fields where mechanical weeding is performed could be positively correlated with adoption as a technology in use, but in particular, its long-term effects over a full production period can be observed under the same local conditions.

2.3 | Endogeneity and reverse causality in peer effects

We depict our theoretical assumptions in Figure 1. As shown by the arrows in both directions, we emphasize the possibility of reverse causality. While most peer effects research focuses on the causal effect of peers' adoption behavior on the adoption decision of the individual farmer, the direction of the effect can also be reverse: Farmers might first adopt a technology and then broaden their social network and engage in information exchange. Examples of such behavior include access to chat groups upon the adoption of a certain app or software (Wims & Byrne, 2015), access to machinery rings upon the adoption of a certain machinery, or access to groups that exchange the experience with a certain farming practice (Chaudhuri et al., 2021). Further, there is evidence that (early) adopters of technology tend to communicate about it to gain social recognition (Shikuku et al., 2019), which shows that information dissemination behavior might change *after* technology adoption.

Another obstacle in identifying peer effects is endogeneity in the network formation process (Bramoullé et al., 2020). Individuals might actively choose their own peer group, leading to selection bias (Blasch et al., 2020; Krishnan & Patnam, 2014; Skaalsveen et al., 2020). Individuals tend to be more willing to connect with others who are

similar, a phenomenon known as homophily (McPherson et al., 2001). In our case, farmers who are most interested in mechanical weeding could actively search for information themselves by joining networking events or by engaging a lot with like-minded farmers before and after the adoption.

Lastly, the relationship between verbal exchange and field observation might also be prone to endogeneity, as observing a field might induce talking to the respective farmer and the other way around. While it is difficult to control for reverse causality and endogeneity, we are merely interested in the correlation and do not aim for causal inference. We aim to investigate in how far adoption is associated with peers' adoption and how the two types of peer effects relate to each other, irrespective of the causal direction.

2.4 | Hypotheses

Against this background, we formulate our hypotheses, as also depicted in Figure 1.

Hypothesis 1a. Knowing at least one other farmer doing mechanical weeding is positively related to having adopted mechanical weeding.

Hypothesis 1b. Observing at least one field where mechanical weeding is done is positively related to having adopted mechanical weeding.

Hypothesis 2. Verbal information exchange and field observation as two types of peer effects complement each other in explaining the adoption decision.

Hypothesis 3. Verbal information exchange and field observation reinforce each other, such that the correlation with adoption is higher for an increasing number of adopters known, for an increasing number of fields observed, and for a decreasing distance to these fields.

3 | METHOD AND DATA

3.1 | Survey design and implementation

To answer our research questions, we conducted an online survey among German sugar beet farmers in early 2022. We designed and implemented a custom-built survey tool, allowing us to obtain explicit spatial data. In this survey, farmers were asked to specify whether, which, and since when they used mechanical weeding techniques. The participants indicated how many other farmers whom they knew used mechanical weeding and were then asked to

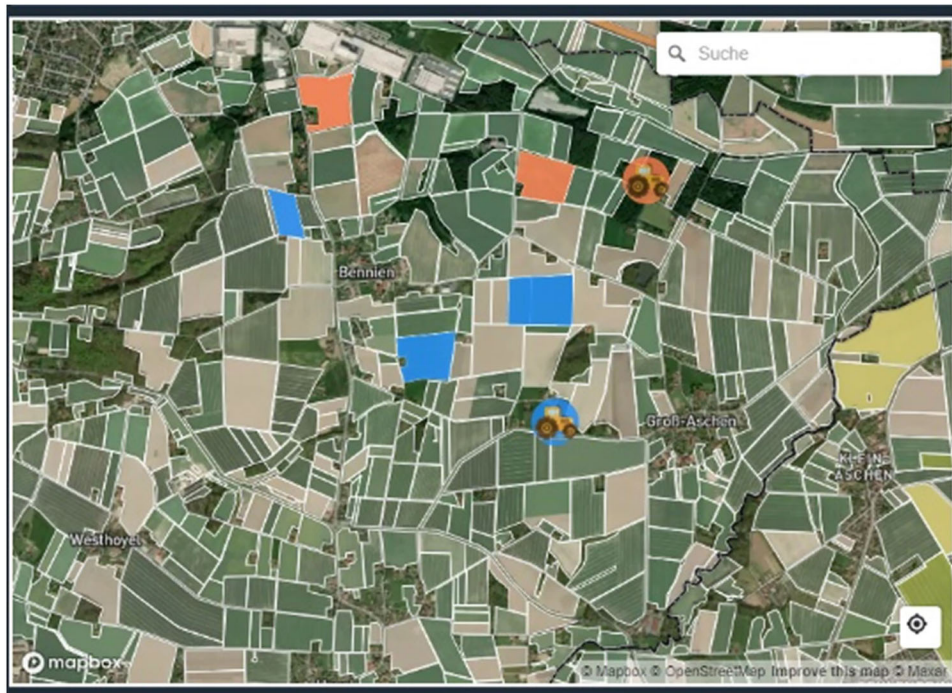


FIGURE 2 Novel custom-build survey tool.

Note: Orange areas indicate own fields, and blue areas indicate other farmers' fields where mechanical weeding was observed (example).

show on an interactive map where they were growing sugar beets and to indicate fields of other farmers where mechanical weeding is done (whether in sugar beet or other crops). As an alternative for those who did not wish to use the map to provide the precise geolocation of fields, participants were asked to give their postal code and select via a single-choice question how many fields they knew of where mechanical weeding is done. For those who did not use mechanical weeding, we asked for the reason for this. All of the participants were asked about their intention to use new weeding technologies in upcoming years. For the map shown in the survey, we used freely available geo-data on field shapes for certain federal states of Germany, as well as remote sensing data from Copernicus for the remaining federal states (for more information, see the original survey in the Appendix). Using this, participants could select their own or others' fields, either by clicking on the fields or by setting a marker (tractor symbol) (Figure 2).

3.2 | Preregistration and sampling strategy

We pre-registered this study using the Open Science Framework (OSF) platform on February 10, 2022, the day we began the data collection (Massfeller & Storm, 2022). In this preregistration, we described our study plan, including

research questions and hypotheses, study design and sampling strategy, and the variables and models used for the analysis (more information on the preregistration, including how and why we deviated from it, can be found in the Appendix). We relied on a convenience sample, as we published advertisements off- and online, as well as cooperated with the advisory network of the German sugar beet industry, the Institute for sugar beet research (IFZ), and a market research company. In the preregistration, we present an a priori power analysis and describe how we would deal with a potentially biased sample. The code used for the analysis can be found on the author's GitHub page.²

3.3 | Empirical approach

3.3.1 | Reflection problem and potential biases

The identification of peer effects is challenging, as an individual's and peers' behavior may correlate for several reasons (Di Falco et al., 2020; Krishnan & Patnam, 2014; Manski, 1993). Manski (1993) differentiates between three possible effects:

² [AnnaMassfeller/SugarbeetSurveyAnalysis](https://github.com/AnnaMassfeller/SugarbeetSurveyAnalysis) (github.com)

- a) endogenous effects, wherein the propensity of an individual to behave in some way varies with the behavior of the group; additionally, the behavior of the group could be impacted by the behavior of the individual,
- b) exogenous (contextual) effects, wherein the propensity of an individual to behave in some way varies with the exogenous characteristics of the group; and
- c) correlated effects, in which individuals in a given group tend to behave similarly because they have similar individual characteristics or face similar institutional environments.

While we are interested in the endogenous effects, that is, the correlation between the peers' and the own adoption decision through field observation and/or knowing adopters, we assume that to address our research question, the differentiation between social (that is endogenous and exogenous effects) and correlated effects is the main necessary and sufficient point. The main challenge is to prevent bias from correlated effects. In the following, we describe how not controlling for correlated and (to a lesser extent) exogenous effects would lead to an overestimation of social effects and how we try to limit such distortion.

Examples of correlated effects are similar natural production conditions (soil quality, topography, etc.) as they could favor or disfavor mechanical weeding, shared advisory services that communicate a certain attitude toward different weed management decisions, contractors that offer a specific type of machinery, or demonstration farms that support certain farming practices. Further, social norms, such as environmental concerns among the wider community, could lead to correlated effects if farmers' behavior differs in response to these concerns. These effects can lead to a correlation between an individual's and peers' adoption. Not controlling for these correlated effects risks overestimating peer effects.

A possible example of exogenous effects based on peers' characteristics could be the peers' experience with the technology or access to machines, for example, depending on the structure of the peers' farms and its specialization, machinery might still be available but not in use, making it free for borrowing. Here, even if neighbors (currently) do not use the technology, they can impact adoption by lending the relevant technology. As we are merely interested in the correlation between verbal exchange and field observation as two types of peer effects and adoption, to provide a first indication of their relative importance and difference, the main challenge is to reduce bias from potentially correlated effects and to isolate the social (endogenous and exogenous) effects.

In our model, information on other adopters (*KnowAdopters*) is used to approximate the possibility of

(verbal) information exchange with adopters. Similarly, the knowledge of mechanically weeded fields from others (*ObserveFields*) provides information on the awareness of other fields (see formulation of relevant questions for *KnowAdopters* and *ObserveFields* in the original survey in the Appendix). Both variables are coded in our model as binary variables with 1 if other adopters are known/fields are observed, respectively, and 0 if not. We denote farmer i 's indication to adopt mechanical weeding by *Adopt*, modelled as a binary decision, taking 1 if mechanical weeding is applied and 0 if not. We include a vector of control variables *Control* containing farmers' characteristics such as age (1 if > 45 years), farm size (1 if > 50 ha), and, to approach environmental attitude, previous participation in agri-environmental schemes (AES) (1 if yes) as binary dummy variables. Additionally, to account for the possible correlated effects, we include (1) the minimal distance to demonstration farms (also squared) as a continuous variable. This reflects the minimal distance of the farm i to a farm belonging to the network of demonstration farms for organic agriculture that are found all over Germany.³ We include affiliation with one of the 19 German sugar factories as a dummy variable in *Control*. Thereby, we can account for regional differences as well as for the effect of farm advisors. To do this, we calculate the distance for each farm i to each of the German sugar factories and assume that farm i delivers to the closest factory. There are 19 sugar factories in Germany, belonging to four sugar producers. We aggregated the factories into 13 groups to avoid very small dummy groups (Figure A1 in the Appendix). We proxy potential exogenous effects by including farm-demographic data at the county level, such as average farm size per county (DESTATIS, 2022a). As it was found that larger farms tend to be more likely to adopt novel technologies (Shang et al., 2021), we assume that farm size is a good approximation for peers' experience with technology or access to machinery. We further include a large number of soil- and topography-related variables at the county level that allow controlling for possible exogenous and correlated effects, as noted above. All variables included in the model are presented in Table 1.

3.3.2 | Least Absolute Shrinkage and Selection Operator (LASSO) double selection

Due to the large number of control variables in a quite small sample, there is a certain danger that parameter

³ More information and a map can be found here: <https://www.oekolandbau.de/bio-im-alltag/bio-erleben/demonstrationsbetriebe-oekologischer-landbau/>

TABLE 1 List of variables in the model specifications.

	Name	Label	Values	Mean
Dependent variable	Adopt	Adoption mechanical weeding binary	'0' '1'	
As in pre-registration [†]	ObserveFields	observing fields binary	'0' '1'	
	KnowAdopters	knowing adopters binary	'0' '1'	
	MinDist_demo	minimal distance to demonstration farm	Num: .44 to 70.76	21.25
	Farmsize	farm size in ha over 50 binary		
	AES	participation in AES binary	'0' '1'	
	Age	farmer age over 45 binary	'0' '1'	
	FactoryLocation_agg	sugar factory location aggregated, dummy	19 locations as in Figure A1 in the Appendix, aggregated to 13	
Instrumental variables [‡]	ShareOrgFarms	Share of organic farms in all farms at county level	Num: 0 to .32	.06
	ShareOrgArea	Share of organic area in utilized agricultural area (UAA) at county level	Num: 0 to .36	.05
Additional variables in Control	Farm_organic	farm organic binary	'0' '1'	
	Mainly_crop	farm specialized in arable farming binary	'0' '1'	
	MeanFarmSize	mean farm size at county level in ha	Num: 18.20–336.5	59.87
	Populationdensity	habitants per km ² at county level	Num: 36–3077	237.62
	FarmDens	farms per km ² at county level	Num: .16–1.99	1.07
	AreaDens	UAA per total county area in ha	Num: .14–.71	.51
	ShareSmallFarms	share of small farms (< 10 ha) in all farms at county level	Num: .06–.53	.22
	ShareSmallArea	share of area of farms with < 10 ha in total UAA	Num: 273.08–23355.4	1041.8
	Elevation_in_m_mean	mean elevation at county or field level [§]	Num: 12–533.4	252.98
	Sand_content_percent_mean	mean sand content in soil at county or field level, in %	Num: .54–82.06	28.68
	Clay_content_percent_mean	mean clay content in soil at county or field level, in %	Num: 5.44–35.61	20.95
	Slope_in_degrees_mean	mean slope at county or field level, in %	Num: .11–13.54	2.6
	ShareArableUAA	share of arable area in total UAA in ha	Num: 31.76–100.6	80.53
	ShareArableInTotalArea	share of arable area in total county area in ha	Num: 8.14–67.6	41.74
Alternative to “factory location”	Association_agg	producer associations aggregated, dummy	10 associations as in Figure A1 in the Appendix	

[†]We describe in the Appendix where and why we partially deviated from the preregistration.

[‡]Part of *Control*.

[§]If the geo-coordinates of the fields are available, soil-related variables are included at field level, for all others, the county mean is taken.

estimates exhibit very high variance and hence could not be trusted. Therefore, we need to reduce dimensionality through variable selection (Labovitz, 1965). Instead of selecting variables based on literature or experience, we follow the state-of-the-art (Storm et al., 2019) and opted

for LASSO (Finch & Hernandez Finch, 2016) and apply a double selection approach based on Belloni et al. (2014).⁴

⁴We tried two other empirical approaches, a simple model that we also preregistered and an instrumental variable approach. However,

Initially developed for prediction purposes, the machine learning tool allows one to consider many explanatory variables in different functional forms and then use the data to identify the ones with the most explanatory power.

However, as we're interested in the correlation between our variables of interest, *KnowAdopters* and *ObserveFields*, and the adoption decision, we need to apply the double selection procedure (Belloni et al., 2014), to avoid the variables being dropped if they're highly correlated to the variables of interest. For example, variables included to capture exogenous effects, for example, farm-demographic structures, might also be correlated with our variables of interest, *KnowAdopters* and *ObserveFields*. In a classical LASSO application, these variables would not be selected, as their explanatory contributions are indirectly captured in *KnowAdopters* and *ObserveFields*. In other words, we need to account for the relationship between our variables of interest and the other control variables. Not selecting those variables explaining our variables of interest might lead to omitted variable bias, and the effect of those variables will be incorrectly attributed to the variables of interest. The same could happen the other way around when only variables are selected with a large effect on our variables of interest but a small effect on the outcome.

Therefore, we follow Belloni et al. (2014) and apply a double-selection procedure. The idea is to select variables that are relevant for both the key variables of interest and the outcome. The union of these sets of selected variables is then regressed on the outcome. The LASSO double selection still relies on the assumption that we have no unobserved confounders (i.e., that all relevant variables are captured in our vector of control variables *Control*). We note that this is a strong assumption and come back to it in the limitations.

We are interested in estimating β_1 and β_2 as depicted in the following base LASSO model (LM_{base}):

$$Adopt_i = \beta_0 + \beta_1 KnowAdopters_i + \beta_2 ObserveFields_i + \delta_i Control_{Adopt} + \zeta_i \quad (1)$$

where $E[\zeta_i | Info_i, ObserveFields_i, Control_{Adopt,i}, r_{Adopt,i}] = 0$, δ_i is a p -dimensional vector with unknown coefficients for the p controls where $p \gg n$ is allowed but not met in our case, and the parameters of interest are β_1 and β_2 , with the effect of *KnowAdopters* and *ObserveFields* on *Adopt*.

In the first step of the double-selection procedure, we run three LASSO models for *Adopt* (LM_1), *KnowAdopters* (LM_2), and *ObserveFields*

(LM_3) as dependent variables, respectively, each time regressed on a vector of control variables *ControlExogenousAdopt*, *ControlExogenousKnowAdopters*, and *ControlExogenousObserveFields*, always excluding the particular dependent variable. We use the R package *glmnet* which allows us to use LASSO for binary response variables via maximum likelihood estimation (Friedman et al., 2010; Simon et al., 2011).

$$LM1 : Adopt_i = \delta_i ControlExogenous_{Adopt,i} + r_{Adopt,i} + \zeta_i \quad (2)$$

$$LM2 : Info_i = \delta_i ControlExogenous_{KnowAdopters,i} + r_{KnowAdopters,i} + v_i \quad (3)$$

$$LM3 : Field_i = \delta_i ControlExogenous_{ObserveFields,i} + r_{ObserveFields,i} + u_i \quad (4)$$

with $E[\zeta_i | ControlExogenous_{Adopt,i}, r_{Adopt,i}] = 0$, $E[v_i | ControlExogenous_{KnowAdopters,i}, r_{KnowAdopters,i}] = 0$ and $E[u_i | ControlExogenous_{ObserveFields,i}, r_{ObserveFields,i}] = 0$.

We identify the variables that have been chosen in this first step for the three different models (see Table A1 in the Appendix). We focus on the variables chosen for the case where the misclassification error is lowest, that is, Lambda.min.

In the second step, we use maximum likelihood to regress *Adopt* on the union of all variables selected for LM_1 , LM_2 , and LM_3 named *Controls_{LM1}*, *Controls_{LM2}*, and *Controls_{LM3}*, respectively, leading to the following final LASSO double-selection model LM_{final} :

$$Adopt_i = \delta_i (\beta_1 Control_{LM1} + \beta_2 Control_{LM2} + Control_{LM3}) + (\beta_1 r_{KnowAdopters,i} + \beta_2 r_{ObserveFields,i} + r_{Adopt,i}) + (\beta_1 v_i + \beta_2 u_i + \zeta_i) = \delta_i \pi + r_{ci} + \eta_i \quad (5)$$

where $E[\eta_i | \delta_i, r_{ci}] = 0$ and r_{ci} is a composite approximation error.

3.3.3 | Do the two types complement each other in explaining the adoption decision?

To identify whether the two types complement each other in terms of explaining the adoption decision (H2), we look at the explanatory contribution of the variables we use to construct (verbal) information exchange and field observation. This is done to identify how the percentage of correct

both approaches exhibit limitations as explained in the Appendix and therefore we decided for the LASSO double selection procedure.

predictions of the adoption decision (prediction accuracy) varies in relation to whether the variables for only one or both types of peer effects are included. If the inclusion of variables for both types of peer effects increases prediction accuracy, we can conclude that different aspects can be explained by their means, indicating complementarity. For this, we compare predication accuracy between different models in which the dependent variable is always the adoption decision and a vector of control variables is included as in the simple pre-registered model (see Appendix for details on this model). As explanatory variables, the different models include our different constructs measuring field observation (a) binary as *ObserveFields* or (b) as number of fields observed (*NrFields*), with the levels “no fields observed” (reference category), “1–5 fields observed,” “6–10 fields observed,” and “> 10 fields observed,” or (c) as distance to fields observed (*FieldDist*⁵), with the levels “no fields observed” (reference category), “fields in 0–5 km distance observed,” “fields in 6–10 km distance observed,” “fields in 11–30 km distance observed,” and “fields in > 30 km distance observed.” Similarly, knowing adopters are measured (a) as a binary with *KnowAdopters* or (b) as number of adopters known (*NrAdopters*), with the levels “no adopters known” (reference category), “1–5 adopters known,” “6–10 adopters known,” and “> 10 adopters known.” Each variable is depicted once alone and then also in combination with each other, together with the vector of control variables *Control*. We compare the results to a model that includes only an intercept (naïve model) and one that includes only the control variables, leading to 14 models overall that we compare (see Table 3 in Section 4.3).

3.3.4 | How do the two types relate to each other within the relevant socio-spatial network?

To determine whether the two types reinforced each other, we examined the predicted likelihood of adoption, given the interaction of *NrFields*, *FieldDist*, and *NrAdopters*. From H3, we expect the likelihood of adoption to be highest where many adopters are known and many fields are observed in close spatial proximity. We also intend to derive the relevant size (*NrAdopters*, *NrFields*) and structure (*FieldDist*) of the network. We take our simple preregistration model (see Appendix for details) and replace the binary variables *KnowAdopters* and *Observe-*

Fields with interaction terms of the different variables measuring field observation and knowing adopters leading to the following three probit interaction models IM₁, IM₂, and IM₃:

$$\begin{aligned} \Pr(\text{Adopt}_i = 1 | \text{NrAdopters_agg}_i, \text{NrFields}_i, \text{Control}_i, \beta, \gamma) \\ = \Phi(\beta_0 + \beta_1 \text{NrAdopters_agg}_i + \beta_2 \text{NrFields}_i \\ + \beta_3 \text{NrAdopters_agg}_i * \text{NrFields}_i + \gamma \text{Control}_i + \varepsilon_i) \end{aligned} \quad (6)$$

$$\begin{aligned} \Pr(\text{Adopt}_i = 1 | \text{NrAdopters_agg}_i, \text{FieldDist_agg}_i, \text{Control}_i, \beta, \gamma) \\ = \Phi(\beta_0 + \beta_1 \text{NrAdopters_agg}_i + \beta_2 \text{FieldDist_agg}_i \\ + \beta_3 \text{NrAdopters_agg}_i * \text{FieldDist_agg}_i + \gamma \text{Control}_i + \varepsilon_i) \end{aligned} \quad (7)$$

$$\begin{aligned} \Pr(\text{Adopt}_i = 1 | \text{NrFields}_i, \text{FieldDist_agg}_i, \text{Control}_i, \beta, \gamma) \\ = \Phi(\beta_0 + \beta_1 \text{NrFields}_i + \beta_2 \text{FieldDist_agg}_i \\ + \beta_3 \text{NrFields}_i * \text{FieldDist_agg}_i + \gamma \text{Control}_i + \varepsilon_i) \end{aligned} \quad (8)$$

where Φ denotes the normal cumulative distribution function, β symbols denote scalars, and γ is a vector of coefficients to be estimated. We estimate the models in (7), (8), and (9) using maximum likelihood. *NrFields* enters as described in Section 3.3.3. To avoid having too many empty and small groups resulting from the interaction terms, we aggregate two levels of the variable *FieldDist*, leading to *FieldDist_agg*, with the following levels: “no fields observed” (reference category), “fields in 0–5 km distance observed,” “fields in 6–10 km distance observed,” and “fields in > 10 km distance observed,” as well as also two levels of *NrAdopters*, leading to *NrAdopters_agg* with the following levels: levels “no adopters known” (reference category), “1–5 adopters known” and “> 5 adopters known.”

4 | RESULTS AND DISCUSSION

4.1 | Descriptive statistics

Our original sample consisted of 313 farmers. After data cleaning, the sample size was reduced to 294 observations that were usable for the analysis.⁶ Following the power analysis reported in the preregistration, we achieved

⁵ We calculated this variable (if not selected directly via single choice question) by taking the mean of the distances between the centroid of the own fields (if chosen via map) or the centroid of the postal code region (if own fields were not chosen via map but only the postal code was given) and the other farmers' fields.

⁶ Due to an error at the beginning of the data collection, spatial data were missing for 18 farms. As there was only one farmer delivering to the

TABLE 2 Sample statistics and comparison with German farm census data from 2020.

Variable	Whole sample (<i>n</i> = 294) Mode [‡] /Mean	Farming census in Germany [†] Mode
Age (in years)	35–44	55–64
Farm size (in ha)	50–99	50–99 [§]
Share of organic farms	5%	2.5% [#]
Number of adopters known	1–5	/
Number of fields observed	1–5	/
Distance to fields observed	0–5	/
Minimal distance to demonstration farms (in km)	21.25	/
Mean distance to fields observed (in km)	7.31	/
Mean distance between own fields (in km, <i>n</i> = 232)	3.73	

[†] Bundesministerium für Ernährung und Landwirtschaft (2021).

[‡] We asked for all demographic variables in categories to not force participants to reveal too concrete information.

[§] Farms with mainly crop production (DESTATIS, 2022a).

[#] Share of organic farms growing sugar beets in all farms growing sugar beets (DESTATIS, 2022b).

a power of .93.⁷ The farmers in our sample are mainly specialized in crop production (74%). Compared to the German farming census from 2020 (see Table 2), the participants in our sample were slightly younger than the German average, a common observation in online surveys (Zahl-Thanem et al., 2021). The farm sizes are within the range of the German average for farms that specialize in crop production. Histograms for the distribution of age and farm size in the sample can be found in the Appendix, Figures A2 and A3. The small share of organic farms in our sample reflects the small market for organic sugar beets in Germany (Eurostat, 2021). Of 294 farmers, 39% (114) reported using mechanical weeding in their sugar beets, 82% (242) knew other adopters, and 85% (251) observed other farmers' fields. The majority of farmers had a rather small and close network, which is in line with earlier findings (Blasch et al., 2020; Conley & Udry, 2010): mostly 1–5 adopters are known, and 1–5 fields are observed at a distance of 0–5 km (mean: 7.31 km), with a distance between the own fields of 0–1 km (see respective histograms in Figure A14). We find a slight difference between those who selected their own and other farmers' fields via the map tool and those using the single-choice question (more on that in the Appendix). Concerning the spatial coverage, our sample well reflects the pattern of the sugar beet farm structure within Germany (see Figure 3).

Most farmers use traditional machinery they own. While previously, the beet hoe was the main tool, machinery

has become slightly more diverse in recent years, and also camera/GPS-steered and autonomous machinery is used (see Figure A6 in the Appendix). Modern and autonomous machinery is more frequently shared with neighboring farms or used via a machinery ring or contractor service (see Figure A7 in the Appendix). The three main reasons that non-adopters gave for not using mechanical weeding are perceived time constraints, perceived low reliability of the technique to efficiently remove all weeds, and high investment costs (see Figure A8 in Appendix). Time constraints could relate to the time to actually do the mechanical weeding (on a tractor), but for future technologies, such as robots, supervision time could play a role (Lowenberg-DeBoer et al., 2021). Hearing of bad experiences from peers or not knowing who to turn to for information on mechanical weeding are among the least important barriers.

4.2 | How do (verbal) information exchange and field observation relate to adoption?

The results from the final LASSO model LM_{final} support our initial Hypothesis 1a: Knowing at least one adopter is associated with a 26% statistically significant higher likelihood of adoption, and Hypothesis 1b: Observing at least one field where mechanical weeding is associated with a 32% statistically significant higher likelihood of adoption, all else being equal (Figure 4). The marginal effects of both variables of interest remain robust in magnitude and significance through all different specifications that underpin trust in our results (see the sensitivity analysis in the Appendix, Figures A8 and A9). We conducted a

sugar factory Cosun Beet Company, we excluded this observation from the analysis to avoid distortion.

⁷ On the chi-squared test for the contingency tables on *Adopt*, and *KnowAdopters*, and *ObserveFields*, respectively, assuming an effect size *w* of .22 as in Di Falco et al. (2020) and an alpha of .05.

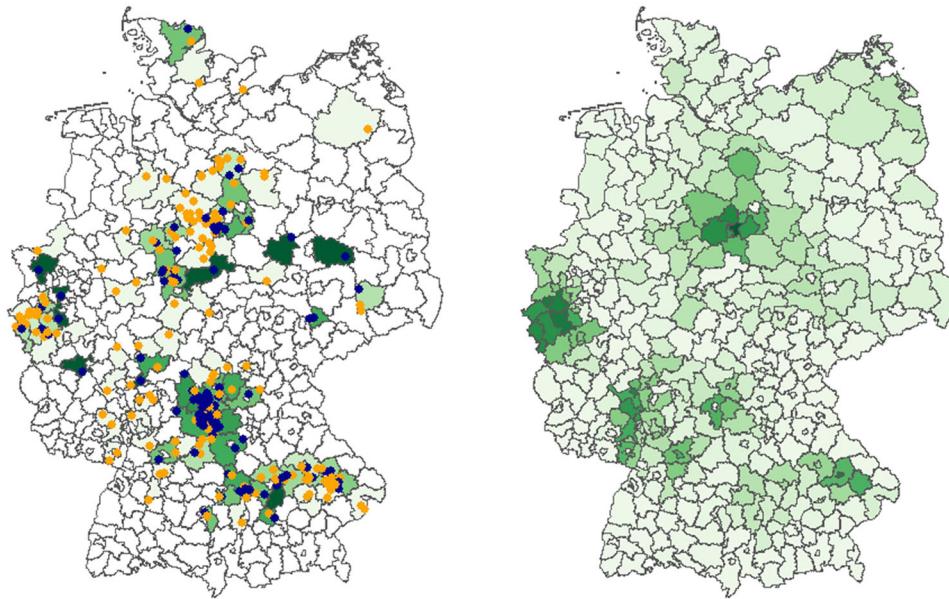


FIGURE 3 Spatial coverage (left) and sugar beet regions in Germany (right).

Note: Right map: Sampled farms (yellow = non-adopters, blue = adopters, white = no observations, green = share of adopters per county, the darker the more). Left map: Main sugar beet regions (the higher the share of sugar beet in arable utilized agricultural area per county, the darker the region).

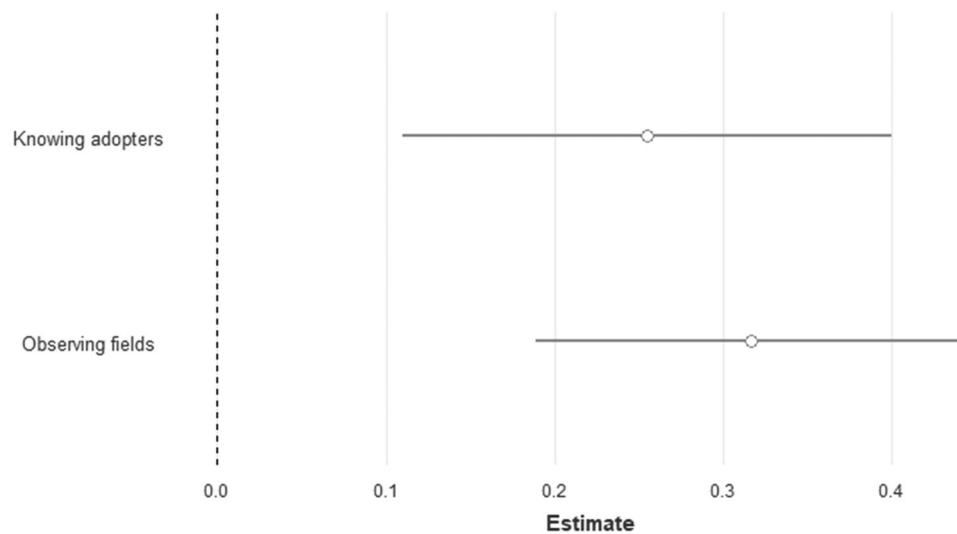


FIGURE 4 Marginal effects for *Knowing Adopters* and *Observing Fields* on *Adoption* of the final LASSO model.

Note: Dependent variable = Adoption, Observations: 294; .95 confidence intervals are displayed, and partial effects for the average observation are given with standardized standard errors.

similar analysis for the intention to adopt, indicating the same direction of effects (see Figures A10 and A11).

Our results on a positive correlation between verbal exchange and field observation and farmers' adoption decisions are in line with similar studies (Mekonnen et al., 2022; Sampson & Perry, 2019). Assuming that a causal relationship underlies the positive correlations between verbal exchange and field observation and farmers' technology adoption decisions, we explain our results by two

phenomena: social learning and social pressure. Prior studies highlight the significance of information scarcity and perceived complexity as key obstacles to adopting new farming technologies (Bakker et al., 2021; Foster & Rosenzweig, 1995; Vecchio et al., 2020). Rogers (2003) underscores the pivotal role of perceived complexity in innovation adoption. Social learning, defined as the process of individuals learning from their neighbors' experiences with new technology Rogers (2003), serves as

a means to mitigate (perceived) complexity by acquiring relevant information from peers. In our case, social learning could occur as mechanical weeding exhibits a certain complexity in implementation and outcome that might hinder adoption, as costs (e.g., labor time) and effectiveness under different local conditions are difficult to predict (Bessette, Wilson et al., 2019; Bessette, Zwickle, & Wilson, 2019; Fishkis et al., 2020; Gage & Schwartz-Lazaro, 2019). Information that reduces the perceived complexity of a technology can either be obtained through verbal exchange (Skaalsveen et al., 2020) but also by observing the technology in use and its results (McCann et al., 2015; Skaalsveen et al., 2020). Kolady et al. (2021) trace the effect of observing fields in a certain radius on farmers' adoption decisions back to the reduction in learning costs and the possibility of deriving information on feasibility in the given local setting. We assume that both types of peer effects transmit different information that both reduce the perceived complexity of mechanical weeding and thereby positively relate to the adoption decision.

We propose social pressure as a second mechanism explaining the positive correlation. Rogers (2003) emphasizes social system norms as a precursor to adoption. Dessart et al. (2019), drawing on Cialdini et al. (1990), distinguish between descriptive (what other people actually do) and injunctive (what people ought to do) norms and signaling motives (to convey some information about oneself to another party), with evidence suggesting their influence on farmers' technology adoption decisions (Dessart et al., 2019; Shang et al., 2021; Streletskaya et al., 2020; Tandogan & Gedikoglu, 2020). Pagliacci et al. (2020) and Gatto et al. (2019) underscore the role of nearby farmers' behavior in inducing social pressure.

For mechanical weeding, we conjecture that descriptive norms may drive adoption if farmers perceive it as the new "norm," influenced by interactions with many adopters or field observations as individuals have a strong wish to conform with this norm if they find themselves in the minority (Asch, 1956). Recent evidence supports the importance of descriptive norms in farmers adopting organic farming (Tran-Nam & Tiet, 2022). Additionally, we suggest that injunctive norms could also trigger adoption but usually require verbal exchange. Empirical evidence has indicated that injunctive norms play an important role in explaining farmers' adoption decisions (Defrancesco et al., 2007; Kuhfuss et al., 2016; Massfeller et al., 2022; Tran-Nam & Tiet, 2022).

Field observations may play a crucial role in signaling motives, allowing farmers to convey their commitment to fellow farmers and the public. The field's condition serves as a symbol of "good farming" (Burton, 2004). This signaling can involve demonstrating environmental stewardship with weedy, likely biodiversity-rich fields, aligning with

findings that environmentally conscious farmers prioritize societal opinions (Defrancesco et al., 2007; Laple & Kelley, 2013). Alternatively, farmers may seek to showcase "success" with weed-free, high-yielding fields. Notably, weed management practices may affect neighboring fields through spillover (herbicides or weed seeds), creating social pressure for farmers to align their practices with those of nearby farmers (Davis & Carter, 2014; Lavoie & Wardropper, 2021; Mac   et al., 2007).

However, as we cannot account for the causal relationship, the reason for the positive relationship between peer effects and adoption could also be based on knowing adopters and observing fields as a *consequence* of the adoption, as farmers might join networking groups to exchange and to visit each other's fields *after* they have adopted, as further discussed in Section 4.3. Further, selection bias in terms of individuals actively choosing their own peer group, preferably consisting of similar individuals (McPherson et al., 2001) could explain the positive relationship between peer behavior and own adoption, as found in similar studies (Blasch et al., 2020; Krishnan & Patnam, 2014; Skaalsveen et al., 2020).

4.3 | How do the two types of peer effects relate to each other?

To identify the contribution of individual, distinct variables to explaining the adoption decision, we explore in how far the percentage of correct predictions changes with or without the variable under consideration (see respective coefficient plots in Figure A13). Table 3 depicts prediction accuracy (i.e., share of correct predictions) of different model specifications (column 2) and the difference to the model with the highest prediction accuracy in increasing order (column 3). With our best model, we can correctly predict the adoption decision for 77.21% of our sampled farmers compared to 61.22% using a naive model.

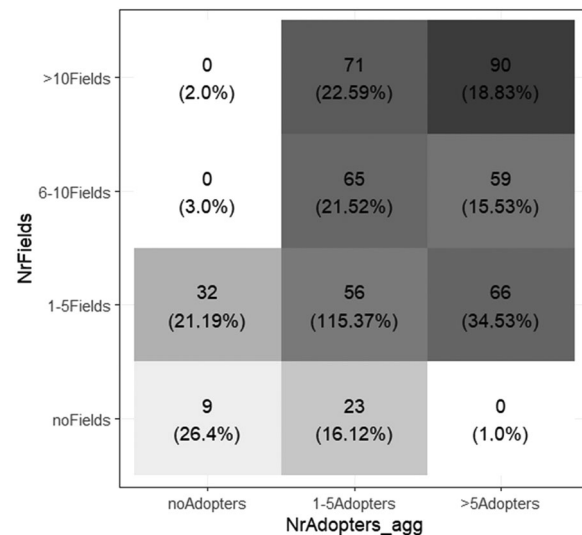
Our results support our complementarity hypothesis (H2): the variables that we use to construct the two types of peer effects contribute to different extents to explaining the adoption decision. We find that the variables used to depict knowing adopters (*KnowAdopters* and *NrAdopters*, models g and k) exhibit a greater explanatory contribution than those related to field observation (*ObserveFields*, *NrFields*, *FieldDist*, models c–f), which could indicate that the former process is more important than the latter. *NrFields* seems to contribute least to an explanation of the adoption decision. A model with only control variables (model b) would predict 68.03% of the choices correctly, which represents a bit more than half of the gain of the full model over the naive model. If a combination of the different variables describing field observation (*ObserveFields*, *NrFields*, *FieldDist*) and knowing adopters (*KnowAdopters*,

TABLE 3 Prediction accuracy of different models.

Model	Prediction accuracy (in %)	Difference from the “best” model (in percentage points)
a) Naïve	61.22	15.99
b) Only Controls	68.03	9.18
and		
c) NrFields	69.39	7.82
d) ObserveFields	71.43	5.78
e) FieldDist and NrFields	71.77	5.44
f) FieldDist	72.45	4.76
g) KnowAdopters	73.81	3.40
h) NrAdopters and NrFields	73.81	3.40
i) KnowAdopters and ObserveFields	74.15	3.06
j) KnowAdopters and NrFields	74.49	2.72
k) NrAdopters	74.83	2.38
l) NrAdopters and ObserveFields	76.19	1.02
m) KnowAdopters and FieldDist	77.21	.00
n) NrAdopters and FieldDist	77.21	.00

NrAdopters) is included (Models h,i,j,l,m,n), the prediction accuracy is highest where *FieldDist* is combined with either *KnowAdopters* (Model m) or *NrAdopters* (Model n) and slightly lower where *NrAdopters* is combined with *ObserveFields* (Model l). It seems that once the distance to fields observed is included, the exact number of adopters known (Model n) does not help explain the adoption decision further; it is enough to include if adopters are known or not (Model m). The combination of a variable that describes field observation and one that describes knowing adopters exhibits higher prediction accuracy (Models h,i,j,l,m,n) compared to a model where only the two field variables are included (model e), underpinning the complementarity hypothesis. We explain the finding on complementarity by the different information that might be delivered. While through verbal information exchange, information on unobservable characteristics can be obtained (e.g. costs), field observation allows to get information on the feasibility of the farming practice under the same production conditions over a full production period.

We further find that of the farmers in the sample, 75% observe fields **and** know adopters, and the adoption share is highest in this group. The lowest share of adopters appears among those neither observing fields nor knowing adopters (8% of the sample) (see Figure A15 in the Appendix). Then, 7% know adopters but do not observe fields, and 10% observe fields but do not know adopters. This indicates that knowing other farmers and observing fields is highly correlated. Exposure to both types is positively related to a higher likelihood of adoption. Being

**FIGURE 5** Predicted likelihood of adoption (in %) dependent on the interaction between the number of adopters known and number of the fields observed (group size and share of adopters in parentheses).

Note: Own presentation based on own data.

exposed to only one or none of these types is very rare and comes with a low likelihood of adoption.

To explore the (combined) effects of knowing adopters and observing fields and to derive the relevant size and structure of the network, Figures 5–7 present heatmaps of the predicted likelihood of adoption (group size and share of adopters) of the three interaction models (see coefficient plots in Appendix, Figure A16) and all possible combina-

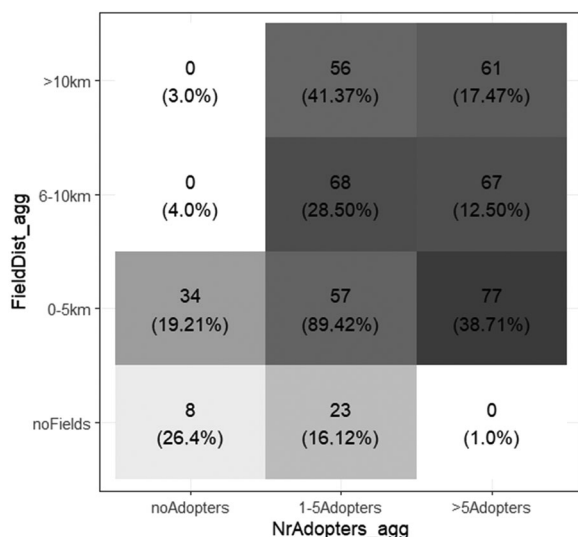


FIGURE 6 Predicted likelihood of adoption (in %) dependent on the interaction between the number of adopters known and distance to fields observed (group size and share of adopters in parentheses).

Note: Own presentation based on own data.

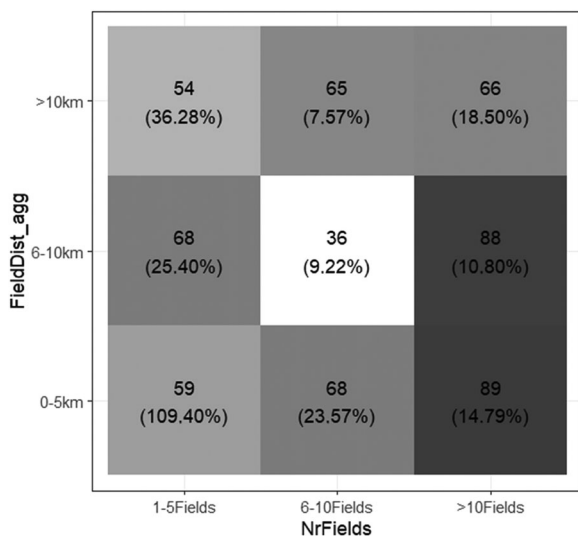


FIGURE 7 Predicted likelihood of adoption (in %) dependent on the interaction between the number of fields observed and distance to fields observed (group size and share of adopters in parentheses).

Note: Own presentation based on own data, Figure 7 based on subsample of “observers.”

tions of the interaction terms, such that the darker the color, the higher the predicted likelihood. We find that the highest predicted likelihood of adoption is exhibited by those who 1) know many adopters and observe many fields: 90% (Figure 5) 2) know many adopters close by: 77% (Figure 6) and 3) observe many fields close by: 89% and 88% (Figure 7).

We find that the highest predicted likelihood of adoption is exhibited by those who

1. know many adopters and observe many fields: 90% (Figure 5)
2. know many adopters close by: 77% (Figure 6)
3. observe many fields close by: 89% and 88% (Figure 7)

These results support our Hypothesis 3, such that the predicted likelihood of adoption correlates positively with the number of adopters known and number of fields observed in close spatial proximity. The two types of peer effects seem to mutually reinforce each other: having a large network among adopters known and many fields observed that are close in terms of spatial radius comes along with a high predicted likelihood of adoption.

Manson et al. (2016) found very similar results for the effect of distance to other farms on the adoption of multi-functional agriculture. Distances below 8 km have a strong impact on the adoption decision, which supports our assumption that local information from farmers and fields facing the same local settings is relevant, likely especially to reduce perceived complexity. This is also reinforced by our finding that the predicted likelihood of adoption increases with the proximity with which a sampled farm is located to a demonstration farm (Figure A20) which was also found in previous research (Wang et al., 2020). Our results indicate that knowing many (> 5) adopters comes along with a high predicted likelihood of adoption, especially if many (> 10) fields are observed, which is in line with Blasch et al. (2020), Genius et al. (2014), and Bandiera & Rasul (2006), who found the same effect for the likelihood of different types of technology adoption. We presume that descriptive norms might explain these patterns: Knowing many adopters of mechanical weeding and observing many fields where it is being used induce the feeling that most farmers are weeding mechanically, leading to a wish to conform with this (perceived) majority (Asch, 1956). If many (> 5) adopters are known (and similarly if many (> 10) fields are observed), the predicted likelihood is highest if the fields are observed close by (0–5 km). This strong effect of knowing many adopters close by on the adoption decision has also been seen in similar studies (Genius et al., 2014; Sampson & Perry, 2019).

While we cannot tell from our data whether the fields observed belong to known adopters, we find a high correlation between the variables we used to construct *NrAdopters_agg*, *NrFields*, and *FieldDist_agg*, respectively (chi-squared tests $p < 1\%$ for all, see Figures A16–A18 in Appendix). Knowing many (> 5) adopters entails observing many (> 10) fields further away (> 10 km). Unlike the revealed importance of local information from fields nearby, we also see a quite high predicted likelihood for

adoption if fields further away are observed, combined with many adopters known (61%) or many fields observed (66%).

In light of these results, we conjecture that endogeneity between the two variables of interest, field observation, and verbal exchange, could be an issue. We cannot rule out that farmers talk to each other more often if their fields are close or that they are more aware of many (close) fields with mechanical weeding if many adopters (= potential respective landowners) are known to them—both observations were made by Mekonnen et al. (2022). In addition, the causal relationship remains unclear; it might simply be that farmers observe a new technology on the field and then approach the farmer to talk about it or that farmers come to know many adopters at a networking event, and after having had a verbal exchange, they visit each other's fields, even further away. Further, throughout our study we rely on the assumption, that the two types of peer effects are based on the same (or highly overlapping) relevant peer group. Nevertheless, both analyses on the relation between verbal exchange and field observation (Table 3 and Figures 5–7) indicate slightly higher importance of verbal exchange compared to field observation when it comes to the adoption decision. We have to keep in mind, that the results rely on the strong assumption of having no unobserved confounders. However, assuming that such confounders would relate to both types of peer effects to a similar extent, we can still make a statement on the *relative* importance of verbal exchange and field observation.

5 | CONCLUSION

The theoretical and empirical understanding of peer effects is a crucial factor for steering farmers adoption behavior of novel, sustainable farming technologies in a desired direction. With this study, we contribute to improve this understanding. First, we add to existing theory by differentiating between two types of peer effects, knowing adopters and observing fields. Second, we empirically investigated the roles and relations of these two different types using a novel survey tool developed for this purpose. We have shown that the LASSO double-selection procedure is helpful in terms of including a large number of variables that allow for control for correlated (and to a lesser extent) exogenous effects, even with a relatively small sample size. Using country-level variables to control for correlated or exogenous effects implicitly assumes that the peer network consists only of peers from the same county. This assumption can indeed be questioned; however, as data on additional characteristics is only available at the country level, this is the best possible approach given the available data.

We find that first, the two variables that we used to approximate verbal information exchange through knowing adopters and field observation both exhibit a positive and statistically significant correlation with adoption. Second, despite the high correlation between the two variables we used to construct our types of peer effects, it remains possible to estimate the correlation of both with adoption indicating a complementary relationship. Third, verbal information exchange seems to be slightly more important in explaining the adoption decision. Finally, the two variables mutually reinforce each other, indicating the importance of a large but spatially close network. The complementary contribution to explaining the adoption decision and the mutual reinforcement of the effects constitute viable findings, even in light of potential endogeneity, reverse causality, and selection bias. Our results provide a clear indication of the importance of differentiating between verbal information exchange and field observation and emphasize the relevance of the *local* production conditions.

Therefore, we advise that future research on farm-level peer effects should distinguish between those arising from verbal exchange and those arising from field observation. Further, the research could test the theoretical assumption of peer effects arising through either social learning and/or social pressure and how the relevance of these two phenomena differs depending on the type of peer effect. In addition, the study of the temporal order of adoption within a certain socio-spatial network could help to identify the causal relationship behind the types of peer effects. We did not account for the relevance of certain peers or groups or if they differ between the two types of peer effects. If our assumption of the two types of peer effects being based on the same (or highly overlapping) relevant peer group is violated, it could impact the relative comparison. Future research could identify the relevant peer groups for each type of peer effect. For example, one could examine whether conventional farmers observe organic fields to understand the usage of mechanical weeding technologies or whether organically farming peers (or their fields) are relevant for either social learning or social pressure, as they might be the first to use novel weeding devices (Shang et al., 2023).

Our results have important policy implications concerning farmers' adoption decisions of new technologies. Based on the finding that verbal exchange seems to be slightly more important for predicting the adoption decision, we derive that advisory services should focus on establishing personal contact between adopters and non-adopters. Given the complementary relationship, field observation possibilities should always be accompanied by the option to verbally exchange, for example, through field days. Following Reichardt et al. (2009, 2009) and Wang et al. (2020), we suggest that training courses on novel technologies in

vocational and technical schools should be combined with practical demonstrations of the new machinery. Policy measures could promote shared ownership of novel technologies, as they seem less likely to be owned alone (Figure A7). This would initiate a (verbal) exchange between like-minded farmers, probably accompanied by joint field observations. In addition, policy measures and extension services could be designed more resource-efficiently by offering a technology to certain farmers in a nearby region for experimental purposes, which would allow the necessary field observation and could be accompanied by the possibility of (organized) verbal exchange with (preferably many) adopters.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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