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When my neighbors matter: Spillover effects in the adoption of large-scale pesticide-free wheat production

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Abstract

We investigate the spillover effects in farmers' adoption decisions of a novel pesticide-free wheat production system. To this end, we exploit the variability and asymmetry in the social ties among neighboring farmers. We find evidence of spillover effects in farmers' adoption decisions as well as in farm and farmer characteristics. Our results further highlight the importance of accounting for potentially heterogeneous social ties in farmer networks beyond pure measures of spatial proximity: spillover effects are only robust once we account for the strength of social ties through farmers' stated tendency to consult peers on agricultural decisions. Our findings highlight the relevance of peer influence in the diffusion of sustainable agriculture practices even in contexts of well-functioned institutions and high interest in environmental protection such as European agriculture. We discuss implications for the design of policies and programs for sustainable agriculture, which are currently in the center of attention in agricultural policymaking.

KEYWORDS

agricultural innovation, pesticide reduction, spillover effects, sustainable agriculture

JEL CLASSIFICATION

O33, Q15, Q16

1 | INTRODUCTION

Reducing the environmental and human health impact of agriculture without compromising food supply is a major challenge for the agricultural sector. Establishing sustainable pest management practices is at the heart of this challenge, with ramifications for food security and sustainability of agriculture. Innovative adaptations in the agricultural systems featuring reductions of harmful input play an important role in agricultural productivity and sustainability (OECD, 2013; Tilman et al., 2011). Farmers' reluctance in switching to new agricultural practices imposes additional challenges for the adaptations to take effect (Le Coent et al., 2021). Understanding the mechanisms for farmers' adoption decisions is, therefore, central for large-scale diffusion of sustainable agricultural systems.

In this article, we investigate farmer's uptake decisions in a novel pesticide-free, but non-organic, wheat production system. It is the first large-scale pesticide-free production program in Europe, breaking new grounds in shifting agricultural production systems towards being

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more environmentally sustainable. In this production system, farmers cannot use synthetic pesticides in wheat production, but can still make use of synthetic fertilizer and are not restricted in pesticide use in other parts of the crop rotation (Möhring & Finger, 2022). Thus, it entails substantially fewer adoption barriers than organic farming, and bears high potential for large-scale sustainable intensification of agriculture (Finger & Möhring, 2022). The relevance of such pesticide-free but non-organic production systems is of increasing relevance in Europe (e.g., Jacquet et al., 2022). Meanwhile, its novelty brings about high levels of uncertainty in production, investment, institution, and marketing. In this setting, farmer networks, in particular exchange of information with peers, can be especially effective in reducing uncertainty and establishing innovative pesticide-free production systems, since peer influence has been shown to play an important role in farmers' adoption of other types of agricultural practices (e.g., Bandiera & Rasul, 2006; Conley & Udry, 2010; Moser & Barrett, 2006). Yet, the relationship between peer influence and individual decision-making in the context of input-reducing adaptations in agriculture has not yet been fully understood (e.g., Yoder et al., 2019).

Farmers' actions and characteristics create spillover effects in the diffusion of innovations on their peers. Spillover effects in peer farmers' actions imply multiplier effects, such that the impact of an intervention can be extended beyond the target group via social interactions (Moffitt, 2001). In the context of agricultural production, spillover effects in farmers' characteristics can also be of interest to policymakers and stakeholders such as industry and non-governmental agencies. This especially applies to characteristics that facilitate or impede farmers' adoption, for instance, peer farmers' relevant experience, knowledge, and/or access to necessary machinery. Presence of spillover effects in these characteristics may inform industry and policymakers in terms of effective provision of infrastructure to facilitate adoption. In the text that follows, we refer to spillover effects in farmers' actions as "peer effects" (i.e., a farmer's adoption decision is influenced by their peers' actions), and spillover effects in farm and farmer characteristics as "contextual effects" (i.e., a farmer's adoption decision is influenced by peers' characteristics such as experience, knowledge, and access to machinery), following terms defined in Manski (1993).[1]

[1] We describe spillover effects with the terminology in the peer effects literature following studies on farmers' adoption decisions of agricultural practices (e.g., Di Falco et al., 2020; Krishnan & Patnam, 2014; Sampson & Perry, 2019). In the spatial econometrics literature (with peers often solely defined by spatial locations), "peer effects" are equivalent to the effects of the spatial lag of the dependent variable when the social matrix has zero-diagonal, and "contextual effects" are equivalent to the effects of the spatial lag of the independent variables.

In the context of novel pesticide-free, but non-organic production systems, these spillover effects are so far undocumented in the literature (e.g., Jacquet et al., 2022).

We here aim to address this gap and investigate the spillover effects in farmers' adoption decisions of pesticide-free wheat production system, especially exploiting the variability and asymmetry in the social ties among neighboring farmers. The focus on pesticide-free production systems particularly contributes to adoption of emerging practices and efforts to reduce or remove harmful inputs in agricultural production. The challenges in designing pesticide-free production programs have recently received substantial attention from the research community (ERA, 2020; PPR, 2021; B. Zimmermann et al., 2021), as well as policymakers in the ongoing policy debates in Europe on reducing the environmental and human health footprints of plant protection, for example, as part of the New Green Deal of the European Union (Möhring et al., 2020). Recent literature has highlighted the importance of the social aspects of farmers' decisions to adopt sustainable practices (Kuhfuss et al., 2016; Läpple et al., 2017; Villamayor-Tomas et al., 2019), in particular, the mechanisms for the social aspects to influence farmers' decision-making still lacks attention (Yoder et al., 2019). Our study furthers the understanding in how far the adoption decisions, experience, knowledge, and machinery from peer farmers could serve as pathways in program and policy designs to increase adoption of pesticide-free production systems. Due to the growing importance of such production systems, we moreover expect our results to lay the ground for the design of pesticide-free production programs in other countries and crops.

Furthermore, our study adds to the literature on the role of social interactions in the diffusion process of innovative agricultural practices. In particular, in addressing the challenges in defining and quantifying information links in peer networks, we combine spatially defined farmer network with farmers' tendency to consult peers on agricultural decisions. This approach allows us to exploit additional variability and asymmetry in information links (and therefore strength of social ties) within a spatial network, which contributes to the relatively small literature that combines information exchange among farmers and spatial effects in understanding technology adoption and diffusion (e.g., Genius et al., 2014).

Our analyses are based on survey data from 1029 wheat growers eligible to participate in the large-scale pesticide-free production program in Switzerland, a country with strong institutional support, well-functioning extension services, and farmers with a high average level of education and relatively high environmental awareness. Our results confirm the importance of accounting for varying information links within farmer networks, which distinguishes our study from studies that rely only on spatial proximity in addressing the role of social interactions in the adoption of agricultural innovations (e.g., Krishnan & Patnam, 2014; Sampson & Perry, 2019; Ward & Pede, 2015).

The remainder of this article is structured as follows: Section 2 provides background of the pesticide-free wheat production system; Section 3 introduces the conceptual background for our analysis; Section 4 presents the empirical strategy; Section 5 describes the data; Section 6 presents the results, followed by discussions; Section 7 concludes.

2 | BACKGROUND ON PESTICIDE-FREE WHEAT PRODUCTION

We focus on farmers' adoption of a novel pesticide-free but non-organic wheat production standard in Switzerland. It is the first program of its kind and is expected to lead to a large-scale reduction of pesticide risks in Switzerland, paving the way for pesticide-free production in other crops and countries. The program was first introduced as a pilot in 2018/19 and is open to all farmers since 2019/20. Farmers substitute pesticide reliance using, for example, (naturally bred) resistant varieties, mechanical weed control, crop rotations and other agronomic measures. In contrast to requirements in organic farming, the pesticide-free wheat program neither restricts the use of artificial fertilizer, nor does it restrict pesticide use in the rest of the crop rotation (see also Böcker et al., 2019; Finger & Möhring, 2022; Möhring & Finger, 2022; for further details). Due to these less stringent requirements, average expected crop yields in pesticide-free production (5.2 t/ha) are higher than in organic production (4.4 t/ha), but lower than in conventional production (7 t/ha) (Möhring & Finger, 2022).

The pesticide-free production system builds on an existing low-input wheat production scheme, which requires farmers to not use any fungicides, growth regulators and insecticides, though herbicide and seed treatment are still allowed (see, e.g., Finger & El Benni, 2013). To switch to the novel pesticide-free production, farmers need to additionally substitute all herbicides and seed treatment, that is, operate fully without synthetic pesticides in wheat production. In this new production system, pesticides are substituted, among others, by adjustments in crop rotations, the use of naturally bred resistant varieties, and mechanical weed control. These requirements might lead to lower yields in pesticide-free production and introduce uncertainty to farmers who have limited information on and experience in such a novel production system. As a compensation, participating farmers receive additional direct payments and price markups for pesticide-free production on top of the existing low-input production scheme (see also Möhring & Finger, 2022, for details). Further supporting the program, the biggest Swiss retailer Migros announced to only sell bread from "pesticide-free" wheat by 2023.[2] On average, the direct payments combined with the price markup are expected to offset the yield losses and additional costs associated with the new production system (Böcker et al., 2019).

The development of pesticide-free production was fueled by strong societal and political debates around pesticides in Switzerland in recent years (Finger, 2021). Moreover, pesticide-free production is specifically in the focus of European agricultural policymaking as a promising pathway to reach policy targets on pesticide reduction (e.g. the "Proteger et cultivar autrement" program in France (Jacquet et al., 2022; PPR, 2021).

To understand the patterns of farmers' adoption decisions, Möhring and Finger (2022) provide, based on the here used survey, a descriptive analysis and a detailed discussion of economic costs and benefits of the program. Findings in the study lay the foundation of understanding the mechanisms that drive individual farmer's decisions to adopt pesticide-free production. However, the underlying mechanisms of adoption, that is, how to best address farmers' expectations of and access to pesticide substitutes, remain unclear. Our study complements the existing study by investigating farmer networks as an important potential driver of adoption of pesticide-free production.

3 | CONCEPTUAL BACKGROUND

Information on uptake of pesticide-free production systems is limited, due to the novelty of these systems on a large scale in Europe. However, encouraging farmers to adopt more environmentally sustainable production systems or participate in agri-environmental schemes via monetary compensations has been a common practice in Europe (see A. Zimmermann & Britz, 2016 for a review). Despite a long history of agri-environmental schemes, well-functioning agricultural extension services, and a general interest in environmental protection among farmers, participation in these schemes in Europe has been limited (Tyllianakis & Martin-Ortega, 2021). Previous literature has investigated a number of factors associated with farmers' adoption decisions in the European setting. While the determinants of adoption depend on the production system or agri-environmental measure (Knowler & Bradshaw, 2007), several factors appear to play a role

[2] This would imply that until 2023 more than 20% of Swiss wheat production will have to be under this production scheme. In 2022 this share is at ca. 10%. See Böcker et al. (2019) and Möhring and Finger (2021) for a detailed overview of both production systems.

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in farmers' adoption decisions. At the individual or farm level, farm and farmer characteristics such as farm size, agronomic conditions, off-farm income, and age, and behavioral factors such as environmental and risk attitudes, contribute to farmers' decision-making (e.g., Dessart et al., 2019; Läpple & Kelley, 2015; Marton & Storm, 2021; Schmidtner et al., 2012). Recent research has also highlighted the relevance of social norms arisen from social interactions in shaping farmers' decision-making (Dessart et al., 2019; Yoder et al., 2019). In particular, social interactions can serve as an important channel for the diffusion of agricultural innovations (Bandiera & Rasul, 2006; Foster & Rosenzweig, 1995). Several studies provide qualitative and quantitative evidence that social interactions may contribute to both positive and negative spillover of adopting environmentally sustainable agricultural production in Europe (Bakker et al., 2021; Läpple & Kelley, 2013, 2015; Marton & Storm, 2021). Yet overall, the social aspect of farmers' decision-making regarding environmentally sustainable practice still requires attention, in particular on the mechanisms that the social aspects influence farmer behavior (Läpple et al., 2017; Yoder et al., 2019).

To illustrate how social interactions could influence farmers' adoption of the pesticide-free wheat production system, we build on the conceptual framework in Möhring and Finger (2022) and discuss how spillover effects could arise from different elements of the framework. Möhring and Finger (2022) propose that farmer i maximizes their expected utility defined by

$$\max_{D_{it}} E\left[U\left(\pi_{it}\left(D_{it}, X_{it}, Env_{it}, \varepsilon_{it}^{D}\right),\ PE_{it}\right)\right] \tag{1}$$

U is the von-Neumann-Morgenstern utility function of the farmer. $\pi_{it}(D_{it}, X_{it}, Env_{it}, \varepsilon_{it}^{D})$ is the profit function, where D_{it} denotes the farmer's adoption decision on the pesticide-free wheat production system, X_{it} contains a set of farm and farmer characteristics related to farm profit, Env_{it} denotes the farm's environmental conditions, which include soil conditions, pest pressure, and weather conditions, and ε_{it}^{D} represents uncertainty in production and depends on the production system (pesticide-free or conventional). PE_{it} denotes the farmer's perception about the pgram that lies beyond the aspects that influence profit, which includes the farmer's behavioral characteristics such as preferences, attitudes, and expectations about the program.

For a utility-maximizing farmer to adopt pesticide-free production, the following condition needs to be satisfied:

$$E\left[U\left(\pi_{it}\left(D_{it}^{D=1}, X_{it}, Env_{it},\ Adj_{it}, \varepsilon_{it}^{D=1}\right),\ PE_{it}\right)\right] \geq E\left[U\left(\pi_{it}\left(D_{it}^{D=0}, X_{it}, Env_{it}, \varepsilon_{it}^{D=0}\right),\ PE_{it}\right)\right]. \tag{2}$$

The left and right side of the inequality denotes the expected utility when the farmer chooses to adopt or not to adopt the pesticide-free wheat production system, respectively. Adj_{it} denotes the adjustment cost associated with switching to the new system.

We extend the framework in Möhring and Finger (2022) by incorporating social interactions into Equation (2), which adapts to:

$$E\left[U\left(\pi_{it}\left(D_{it}^{D=1}, X_{t}, Env_{t},\ Adj_{t}, \varepsilon_{it}^{D=1}\right),\ D_{jt},\ PE_{t}\right)\right] \geq E\left[U\left(\pi_{it}\left(D_{it}^{D=0}, X_{t}, Env_{t}, \varepsilon_{it}^{D=0}\right),\ D_{jt}, PE_{t}\right)\right]. \tag{3}$$

That is, the utility from choosing either production system is not only fluenced by farmers' own adoption decision (D_{it}), characteristics (X_{it}), environmental conditions (Env_{it}), and perceptions about the program (PE_{it}), but also those of their peers', that is, D_{jt}, X_{jt}, Env_{jt}, and PE_{jt}. More specifically, we consider that some peer characteristics (X_{jt}) and environmental conditions (Env_{jt}) influence farmer i's utility through the profit function, and peer adoption decisions (D_{jt}) and perceptions about the program (PE_{jt}) influence farmer i's utility via aspects beyond profit (see more discussions below). Therefore, we drop the subscript i from X_{it}, Env_{it}, and PE_{it} in Equation (2), and additionally incorporate D_{jt} in the utility function. Spillover effects thus entail effects from D_{jt} (peers effects), as well as from X_{jt}, Env_{jt}, and PE_{jt} (contextual effects).

Next, we discuss the elements from which spillover effects may arise. In the context of adopting a sustainable agricultural production system, a particularly relevant mechanism for spillover effects to arise is social conformity. Farmers may adopt an agricultural practice in order to comply with social norms established among fellow farmers (e.g., Bandiera & Rasul, 2006; Chen et al., 2009; Le Coent et al., 2021). In the specific context of reducing pesticide use in agriculture, social norm has also been considered a relevant factor, though it has not been explored quantitatively in the context of a novel program (e.g., Bakker et al., 2021; Pedersen et al., 2012). Due to social norms, farmers may derive utility from choosing practices (e.g., pesticide-free production) similar to their peers, or disutility from non-conforming practices. Such social norms also contribute to explanations of why farmers' behaviors do not strictly follow expected profit maximization, for example, the lack of adoption of certain agricultural practice even in the case of expected increase in profit or financial compensations, and vice versa (Le Conte et al, 2021). Under the framework in Equation (3), social norms could lead to peer effects, that is, spillover effect in farmers' choice of production system, such that farmer i's utility depends on peer farmers' adoption decisions (D_{jt}), particularly how their own choice deviates from the peer group's choices. Social norms could also give rise to contextual effects, namely spillover effects in farmers' perceptions about the program, such that their utility depends on PE_{jt}.

Apart from social norms, spillover effects could also arise due to agglomeration benefits (Bartolini & Vergamini, 2019; Läpple & Kelley, 2013; Lewis et al., 2011). This could apply to areas that share similar soil condition or pest pressure, or neighborhoods where farmers could easily access machineries for the new production system (e.g., via sharing or borrowing). Access to machinery via peers also help reduce the investment uncertainty associated with the new production system. Agglomeration benefits could give rise to both peer effects (D_{jt}) and contextual effects, namely ownership of machinery by peer farmers, which are contained in X_{jt} and therefore X_t, as well as environmental conditions faced by peers, which are contained in Env_t. Furthermore, social learning or knowledge transfer could also help reduce the uncertainty in the costs and benefits of the new production system (Foster & Rosenzweig, 1995; Foster & Rosenzweig, 2010; Genius et al., 2014; Ward & Pede, 2015). Similar to the other sources, social learning could give rise to peers effects (D_{jt}), and contextual effects (X_t, which includes prior knowledge of similar production system).

In terms of defining a peer network, farmers' perceptions about new agricultural practices have been shown to be influenced by their immediate environment, that is, neighboring (spatially proximate) farmers' behaviors and characteristics (Burton et al., 2008; Case, 1992). This arises both because farmers can easily observe practices on neighboring farms, and that information exchange related to agricultural practices occurs conveniently among neighboring farmers (Burton et al., 2008; Burton & Schwarz, 2013; Defrancesco et al., 2018; Moser & Barrett, 2006). As such, spillover effects in the context of agriculture are largely spatially mediated. Accordingly, spillover effects are often assumed to arise through interactions of farmers in peer networks defined by spatial proximity (e.g., Bartolini & Vergamini, 2019; Lewis et al., 2011; Schmidtner et al., 2012; Storm et al., 2015).

Yet, spatial proximity alone does not guarantee an impact on each other's perception or behavior. In particular, the diffusion of innovative technologies and practices also relies on information exchange among farmers, and peer farmers make up a crucial component in farmers' information source (Genius et al., 2014). This is especially relevant for a newly-launched program, where farmers neither have much own prior experience to rely on, nor do they have much observation of the adoption outcomes of other farmers, which would help resolve the uncertainty in the costs and benefits of the new production system. In this case, information exchange with peers could be crucial in reducing uncertainty about adopting the production system. Although spatial proximity does not necessarily guarantee social interaction, and thus information exchange, among farmers (Conley & Udry, 2010), in studies that examine spatially mediated peer effects, it has been a common assumption that information exchange automatically occurs among neighboring farmers (Läpple et al., 2016). An alternative approach that assures information transmission among peer farmers is to use qualitative tools to identify self-reported peers with whom farmers communicate (e.g., Bandiera & Rasul, 2006; Conley & Udry, 2010; Matuschke & Qaim, 2009). Due to the limited number of peers that researchers are able to identify with this type of approach, sampling issues are likely to arise (Blume et al., 2015; Maertens & Barrett, 2013). Furthermore, it is possible to overlook spillover effects in the spatial dimension, which is particularly relevant in the context of agricultural practice. Thus, in investigating the adoption of novel farming practices, accounting for both the spatial dimension of agricultural practices, and information exchange among peer farmers in the network is crucial. Yet, to our knowledge, previous studies have predominantly focused on either one of these two important aspects when measuring social ties (e.g., Krishnan & Patnam, 2014), or account for information exchange only via covariates in the empirical model (e.g., Läpple & Kelley, 2015).

To create a combined measure of social ties incorporating both spatial proximity and the tendency of information exchange regarding agricultural practices, we refine the measurement of social ties in a spatially defined peer network with the tendency for farmers to consult their peers when it comes to agricultural decisions. We extract farmers' response to the statement: "For important agricultural decisions I often consult my neighbors/colleagues," measured on a scale from 1 (does not apply) to 5 (applies perfectly). The intuition for why this variable introduces relevant information regarding social ties in terms of agricultural decisions is as follows: for a farmer relatively more willing to consult peers' opinions, the actions of their peers would be valued more compared to a farmer less willing to consult peer opinion, even if they have the same peers. In other words, this variable captures the extent to which neighbors' opinions actually "matter" to a farmer, and therefore introduces additional variation (on top of spatial proximity) in the weights in the social matrix. The weights in the new social matrix, which contain information on both spatial proximity and farmers' tendency to consult peers on agricultural practices, proxy for social ties in the context of agricultural decisions. The strength of social ties influences how social interactions shape individual (environmental) behavior (Videras et al., 2012). The information on social ties among farmers therefore allows us to assess

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the extent to which spillover effects rely on effective information exchange within farmer peer networks. We discuss the measures of social ties in more details in the next section.

4 | EMPIRICAL STRATEGY

We next empirically analyze the spillover effects discussed under the conceptual framework. Let ω_i be the action of farmer $i, \omega_i \in \{0,1\}$ in the context of adopting the pesticide-free production system, $\omega_i = 1$ if farmer i adopts the system, and 0 otherwise. Following Möhring and Finger (2022), we estimate the following linear probability model $\Pr(\omega_i = 1|x) = x\beta$:

$$\Pr(\omega_i = 1|x) = \beta_0 + \beta_1 x_i + \beta_2 \sum_j c_{ij} x_j^c + \beta_3 \sum_j a_{ij}\omega_j + u_i \tag{4}$$

social matrices $A = \sum_j a_{ij}$ and $C = \sum_j c_{ij}$ define the strengths of social ties between farmer i and peers $j \neq i$ in the network for peer effects contextual effects, respectively. Elements in the social matrices indicate the extent to which farmer i is influenced by each peer j. x_i is a vector of characteristics of i, and x_i^c is a subset of x_i, which comprises characteristics that could influence others' adoption decisions. As such, the parameter $\beta_2 \sum_j c_{ij} x_j^c$ captures the contextual effect, which is a weighted average of peers' characteristics in the network. $\beta_3 \sum_j a_{ij}\omega_j$ captures peer effects, and β_1 captures effects of farmers' own characteristics.

Following Möhring and Finger (2022), we classify farmers who already decided to adopt ("adoption pioneer") or intend to adopt ("intended adopter") the pesticide-free wheat production system in the 2019/20 season as "adopters." That is, $\omega_i = 1$ for both "adoption pioneer" and "intended adopter." For a very recently launched program such as the pesticide-free wheat production system, farmers' intention to adopt the production system also bears implications for understanding the adoption and diffusion of the system. To ensure the estimated spillover effects also apply to realized adoption, we perform robustness checks with separate analyses of realized and intended adoption. We define the strength of social ties in a network of farmers in two ways: based on spatial proximity alone, and based on spatial proximity combined with tendency to consult peers in a network, respectively. Under both setups, we define the peers of each farmer as the 10 nearest neighbors in the main estimation. Under the first setup (only spatial proximity), we define both the social matrices for peer effects $A_1 = \sum_j a_{ij}$ and contextual effects $C_1 = \sum_j c_{ij}$ based on distance between farmers, weighted by inverse distances: $a_{ij} = c_{ij} = d_{ij}$, where d_{ij} is the row-standardized inverse distance weights for farmer i with peers $j = 1 \ldots 10$. In the second setup (spatial proximity and tendency to consult peers), we further scale each row of the peer effects social matrix with the tendency to consult peers on agricultural decisions, which we discuss in the conceptual background section. Let p_i denote this scaling variable, then $A_2 = A_1 \cdot p_i$. To make estimates based on the two social matrices for peer effects comparable, we define p_i as the raw response from the question, which ranges from 1 to 5, divided by the median, 3, such that p_i has a median value of 1. As such, the spatially defined peer effects matrix A_1 corresponds to a case where all farmers have the same tendency to consult peers regarding agricultural decisions (with $p_i = 1$ for all i). The rows of A_2, therefore, do not all sum to 1, but rather depend on p_i. This set up also adds further asymmetry to the strength of social ties between a pair of farmers, which facilitates identifying peer effects (Blume et al., 2015). Figure A1 in the Appendix provides an example with a special case where two farmers have the same peers in their respective networks, yet the social ties with these peers differ due to the difference in their tendency to consult peers.

We separate general farm and farmer characteristics into pure individual characteristics, and characteristics that could potentially generate spillover effects such that they could influence peers' adoption decisions. The former set of variables include land ownership, farm succession, and the fraction of income from non-farming activities. For the general farm and farmer characteristics that could exert contextual effects, we include farmers' age and education, farm size, experience with pesticide-free wheat production, enrollment in soil conservation programs, and accessibility of machinery required to switch to mechanical weed control.[3] We further include farmer behavioral characteristics that are particularly relevant to the pesticide-free wheat program in the set of farmer characteristics that may generate contextual effect. These behavioral characteristics include farmers' perception of potential environmental benefits of pesticide-free production system, openness to innovation, expected yield risk and yield decrease due to the production system, and willingness to take risks in plant protection. Since spatial spillovers are likely to exist in the production conditions, we further control for biophysical characteristics relevant to wheat production, including soil conditions, topography, climate conditions, pest pressure, potential

[3] We note that some covariates already partially capture peer characteristics, for example, the variable access to machinery accounts for access via a neighbor or colleague, and the variable prior experience in herbicide production reflects both personal and others' (neighbor, friend, advisor) experience.

resistances to herbicides, and average wheat yield levels over the past 10 years as contextual effects (the latter two at the municipality and postcode levels, respectively). Finally, since pesticide-free production involves similar production strategies and equipment as organic farming,[4] we control for the density of organic farms in the municipality of each farm. For the set of characteristics with potential spillover effects, we expect both positive and negative spillovers. For example, high value of the environmental and health benefits of a production system may generate a positive spillover to neighbors' willingness to adopt the pesticide-free system, whereas pest pressure can spillover to nearby farms (e.g., through dispersion of seeds by wind) impeding pesticide-free production (Fenichel et al., 2014; Frisvold, 2019).

The estimation of spillover effects often involves a number of econometric challenges. Below we discuss the challenges relevant in our context and our strategies to mitigate such challenges in estimation. The first challenge, termed the reflection problem in the framework of Manski (1993), relates to separately identifying endogenous peer effects and contextual effects. The issue arises when only aggregate data of group behavior and group characteristics are available, or individuals are assumed to interact with all of the others within a peer group and none outside of it, such that the expected group behavior is linearly dependent on the expected group characteristics. As a result, one cannot determine whether an individual's behavior is influenced by the peers, or it is a result of their influence on the peers. As we discuss in the previous sections, in the context of adopting innovative agricultural production systems, both peer effects and contextual effects could potentially facilitate the diffusion of agricultural innovations. Given the different policy implications they bear, however, we are interested in separately estimating the two effects. Previous literature has discussed various conditions with positive identification results under the linear-in-means model (e.g., Blume et al., 2015; Bramoullé et al., 2009; Calvó-Armengol et al., 2009; Davezies et al., 2009; Lee, 2007). Particularly relevant to our context are the conditions discussed in Bramoullé et al. (2009) and Blume et al. (2015) which exploit the variations in individual-specific peer networks. Specifically, Bramoullé et al. (2009) show that the overlaps of individuals' networks create "intransitive triads," such that for an individual i, some of their peers' peers (i.e., those that are two links away from i) are not in i's own network, and they can only influence i indirectly through i's direct peers. Such overlaps allow for linear independence between the social matrices that characterize the direct peer network and the network of indirect peers two links away, that is, C and C^2, both of which can serve as instruments for expected peers' behavior. In our study, overlaps between the individual-specific peer networks exist by definition, which allow us to separately estimate the peer effects and contextual effects as long as the linear independence conditions are met. In the specification of the peer social matrix that incorporates the tendency to consult peers (setup two), the asymmetry in the strength of information links between peers further facilitates identifying the parameters of interest (Blume et al., 2015). We estimate a two-stage least squares model using weighted characteristics of direct peers and indirect peers that are two links away, that is, (X^c, CX^c, C^2X^c), as instruments for peer action.

A second challenge is related to separating spillover effects from correlated effects. Correlated effects can arise due to unobserved common factors that are correlated with the behaviors of individuals in a network, such that the similar behaviors between peers are driven by the common unobservables rather than peer effects or contextual effects. This would lead to omitted variable bias (Goldsmith-Pinkham & Imbens, 2013). We control for a rich set of covariates that could commonly influence multiple individuals in a network as they are spatially correlated and correlate with farmers' decisions to adopt pesticide-free production. These include soil conditions, topography, climate conditions, weed pressure and potential resistances to herbicides. To the extent that there still exist unobserved common factors that lead to similar behaviors of farmers in a network, in the case that the unobserved common factors are not correlated with the formation of links in a network, the issue can be addressed by incorporating network fixed effects (Bramoullé et al., 2009; Lin, 2010). In our context, potential unobserved common effects could arise due to policy measures that support adoption of certain agricultural practices or agri-environmental schemes. Interaction with extension service is another important potential source of influence in farmers' agricultural decision-making (Genius et al., 2014; Wuepper et al., 2021). Extension services are organized at the cantonal level, and could lead to different adoption tendencies across cantons (administrative subdivisions directly below the federal level). We therefore include canton-level network fixed effects. In doing so, we apply a within-group transformation by subtracting the canton averages from the individual-level observed variables, so as to remove the canton-level unobservables.[5] For

[4] For example, the transition from chemical to mechanical weed control requires equipment and knowledge that is available at organic farms.

[5] The within-transformation does not address the case that the common unobservables are also correlated with link formation, that is, sorting into peer networks. In this case, we can consider that all individuals play a two-stage game, first to form peer networks, and then decide on individual behaviors (Blume et al., 2015). In our context, as peer networks are

farmer i in canton k,

$$\Pr(\omega_{ki} = 1|x) = \beta_{0k} + \beta_1 x_{ki} + \beta_2 \sum_j c_{ij} x^c_{kj} + \beta_3 \sum_j a_{ij}\omega_{kj} + u_{ki} \quad (5)$$

Let $K = \frac{1}{n}\iota\iota'$, then $\mathrm{I} - K$ measures deviation from canton averages. We then multiply both sides of Equation (5) with $\mathrm{I} - K$ to apply the within-transformation, writing the transformed equation in matrix form:

$$(\mathrm{I}-K)\Pr(\omega_k = 1|x) = (\mathrm{I}-K)\beta_{0k} + (\mathrm{I}-K)x_k\beta_1 + (\mathrm{I}-K)Cx^c_k\beta_2 + (\mathrm{I}-K)A\omega_k\beta_3 + (\mathrm{I}-K)u_k \quad (6)$$

with the corresponding reduced form

$$(\mathrm{I}-K)\Pr(\omega_k = 1|x) = (\mathrm{I}-K)(\mathrm{I}-A\beta_3)^{-1}\beta_{0k} + (\mathrm{I}-K)(\mathrm{I}-A\beta_3)^{-1}x_k\beta_1 + (\mathrm{I}-K)(\mathrm{I}-A\beta_3)^{-1}Cx^c_k\beta_2 + (\mathrm{I}-K)(\mathrm{I}-A\beta_3)^{-1}u_k \quad (7)$$

Accounting for network fixed effects requires more variation in the network with at least two individuals separated by at least three links (Blume et al., 2015; Bramoullé et al., 2009), and therefore linear independence in C, C^2, and C^3. By the definition of individual-specific peer networks in our context, this requirement is again satisfied in our data. We, therefore, use $(\mathrm{I}-K)x^c_k, (\mathrm{I}-K)Cx^c_k, (\mathrm{I}-K)C^2x^c_k, (\mathrm{I}-K)C^3x^c_k$ as instruments for $(\mathrm{I}-K)A\omega_k$.[6]

It is nonetheless important to note that the strategies we discuss above mitigate but are not guaranteed to eliminate the estimation challenges. Despite of the importance of the spatial dimension for peer effects in agricultural practices, we acknowledge that social interactions can occur beyond the spatially defined peer group. Furthermore, it is possible that confounding factors still exist beyond the dimension we control for unobserved common factors and network fixed effects (i.e., at the municipality, postcode, and cantonal level). In light of these potential issues, we conduct further robustness checks.

primarily defined based on spatial proximity, it is unlikely that the unobservables enter the first stage game (i.e., locating in a neighborhood), and thus sorting is unlikely to be a major concern in this case.

[6] Note that the reduced-form parameters also link to spatial effects of a spatial Durbin model in the spatial econometrics model (see, e.g., Funes et al. 2022; Lapple et al. 2017; Vacaflores & LeSage 2020). As we discuss in footnote 1, in this study we adhere to estimation strategy and terminologies from the peer effects literature because we are interested in the structural parameters that characterize peer effects and contextual effects. Nonetheless, we estimate a spatial Durbin model as a robustness check.

4.1 | Robustness checks

To test the robustness of the estimates from our main specification, we estimate a number of alternative specifications in terms of variable definition, social matrix definition, sample, model specification, and estimation methods. First, in our main specification, the dependent variable contains both realized adoption ("adoption pioneers") and intended adoption ("intended adopters"). To examine whether spillover effects differ between the two types of adopters, we conduct separate analyses with the dependent variable only coded 1 (= adoption) for adoption pioneers or for intended adopters, respectively. Second, to make sure the estimates do not rely on the chosen number of peers, we estimate the same models but with the networks defined as the six and 15 nearest neighbors respectively, instead of 10 in the main analysis. We also use an alternative definition of spatial neighbors with all farmers within a 10 km radius are considered as peers (under this definition, 13 farms did not have any neighbors within the radius, and thus they were removed from the analysis). Third, we estimate the models (with peer networks of 10 nearest neighbors) with a subsample in which we exclude farmers who indicated that they were not aware of the pesticide-free wheat program, as well as subsamples separated by farmers' primary language (French or German, the two major language regions in the study area). Fourth, since some behavioral characteristics may be correlated with farmers' tendency to consult peers or other behavioral variables available in the survey, we estimate the models alternative sets of behavioral characteristics (detailed descriptions in the Results and Discussion Section). We further test whether spillover effects are mediated by the behavioral characteristic openness to innovation. We do so by carrying out a sequential g-estimation following Acharya et al. (2016). Fifth, for comparison to the two-stage least squares estimation, we also estimate linear probability models with ordinary least squares estimation and probit models. Finally, while we focus on estimation strategy from the peer effects literature, we expect that the estimated relationship between peer adoption/characteristics and individual adoption decision should agree with estimates from spatial econometric models, which are also often used to estimate spillover effects in technology adoption (e.g., Funes et al., 2022; Lapple et al., 2017). We, therefore, estimate an unconstrained spatial Durbin probit model as a robustness check of the overall estimation strategy.

5 | DATA

Our primary data source is an online survey conducted with all IP-SUISSE wheat producers. The survey was conducted between December 2019 and January 2020, with 1105 complete responses out of a total number of 4749 IP-SUISSE wheat producers. The sample of respondents are representative of the population of IP-SUISSE wheat producers in terms of spatial distribution and structural farm and farmer characteristics, with average delivered wheat slightly higher than the population average (Möhring & Finger, 2022).[7] The survey contains information on farmers' adoption decisions for the 2019/2020 season and perceptions regarding the pesticide-free wheat program, farm and farmer characteristics that are potentially relevant to the adoption decision, as well as farmer behavioral characteristics.

We supplement the survey with the following data sources: information on weed pressure in the study area (Info Flora), the spread of herbicide resistance (Agroscope), climate conditions (MeteoSuisse), and soil conditions and the density of organic farming (Swiss Federal Office for Agriculture [FOAG]). Except for herbicide resistance and organic farming density, which is measured at the municipality level, all other variables are measured at the farm level. In addition, we match average Extenso wheat yield over the past 10 years at the postcode level to proxy the local production potential. The dataset is publicly available and described in more detail in Möhring and Finger (2022a).

Since extension services and various layers of farmer exchange are organized at the cantonal level, we assume social interactions primarily take place in farmer networks within the same canton (see detailed discussion in the Empirical Strategy section). To ensure a sufficient number of peers in a farmer's network, we restrict the sample to cantons with at least 20 respondents, which results in a sample of 1036 farms. We further exclude seven farms whose reported canton name does not match the coordinates. This leaves us with a final sample of 1029 farms.

5.1 | Descriptive statistics

Table 1 provides description and summary statistics of the variables in the analysis. Figure 1 shows the distribution of farmers' adoption decisions and their tendency to consult peers when it comes to decisions in agricultural practices. Almost 60 percent of farmers in our sample indicated realized or intended adoption, out of which 13.4% adopted the program in the 2019/20 season (138 farms—"adoption pioneers"), and 43.7% intended to adopt at the time of the survey (450 farms—"intended adopters"). We also observe substantial heterogeneity in farmers' tendency to consult peers on agricultural decisions, though a clear spatial pattern does not appear.

[7] Möhring and Finger (2022) discuss that the slight deviation does not affect the conclusion regarding pesticide-free wheat production based on the sample. See also Finger and Möhring (2022) for another application of this dataset.

6 | RESULTS AND DISCUSSION

Table 2 reports the main estimation results (from the second stage of the two-stage least squares model regression; results from the first stage regressions are reported in Table A1 in the Appendix). In models (1) and (3), weights in the social matrix are based on spatial proximity, and in models (2) and (4), the weights are further scaled by farmers' tendency to consult peers when it comes to agricultural decisions. In models (1) and (2), we include general farm and farmer characteristics, and biophysical conditions related to pesticide-free wheat production (see the Empirical Strategy section). In models (3) and (4), we further add farmer behavioral characteristics specific to the pesticide-free wheat program.

With only general farm and farmer characteristics and biophysical conditions included (models (1) and (2)), we find no peer effects when social interaction is measured merely by spatial proximity. By contrast, when we incorporate farmers' tendency to consult peers in the measure of social interactions, we find statistically significant peer effects in adopting pesticide-free wheat production. For a farmer with an average tendency to consult peers regarding agricultural decisions (i.e., with a value of 1 in the scaled variable), an additional peer willing to adopt the program is associated with 2.3 percentage points higher probability of adoption. Equivalently, a farmer with all (10) peers willing to adopt the program has a 23 percentage points higher probability to adopt compared to a farmer with no peers willing to adopt. The peer effects for farmers with other levels of tendency to consult peers can be calculated by scaling the coefficient estimate. For example, for a farmer with the highest possible level of tendency to consult peers (i.e., 1.67 times of the mean value), an additional peer adopting the program would increase their probability to adopt by 3.8 percentage points. As we include farmer behavioral characteristics in models (3) and (4), we find positive peer effects with both measures of social interactions. From our preferred specification in model (4), an additional peer willing to adopt the program is associated with 1.8 percentage points higher probability of adoption.

We also find evidence of contextual effects in some farm and farmer characteristics. In model (3), a one-unit increase (on a scale of 0 to 10) in the average willingness to take risks in the plant protection domain of a farmer's

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TABLE 1 Variable description and summary statistics.

Variables	Type/Unit	Description	Mean	Std.Dev.	Median
Adoption decision	Binary	=1: Will or intend to adopt the pesticide-free wheat program	.6	.5	1.0
Tendency to consult peers	Scale 1-5	Consult peers for agricultural decision-making	2.6	1.1	3.0
		=1: does not apply; =5: applies perfectly			
General farm and farmer characteristics					
Age	Year	Age of farmers	47.0	9.3	48.0
Education	Binary	=1: Has higher education	.1	.3	.0
Agricultural land	ha	Agricultural land in hectares	33.9	20.6	28.5
Wheat share	Ratio	Share of wheat on agricultural land	.2	.1	.2
Workforce	Working units	Working units employed on the farm (equals 280 working days)	1.6	1.0	1.5
Language	Categorical	=1: German; =2: French	1.2	.4	1.0
Leased land	Ratio	Share of leased land	.3	.3	.3
Farm succession	Binary	=1: Farm succession not yet established	.3	.5	.0
Off-farm income	Ratio	Share of off-farm income	.2	.2	.1
Soil conservation	Binary	=1: Enrolled in at least one soil conservation program	.6	.5	1.0
Machine	Binary	=1: Have access to Machinery for pesticide-free production (mechanical weed control)	.2	.4	.0
Experience	Binary	=1: Prior experience with herbicide-free production	.8	.4	1.0
Biophysical conditions					
Mean yield	dt/ha	Mean Extenso yield in the municipality 2008-2018	51.3	4.7	51.5
Organic share	Ratio	Share of organic farms in the municipality	.0	.1	.0
Problematic weed	Ratio	Share of herbicide resistant weed varieties present in the municipality	.5	.3	.5
Suitability for grain	Scale 0-2	Suitability of soil for grain production	.8	.7	1.0
Suitability of slope	Scale 0-2	Suitability of land for agricultural production regarding its topography	1.3	.9	2.0
Temperature	Centigrade	Average yearly mean temperatures on the farm over the last 10 years	9.0	.6	9.0
Precipitation	l/m^2	Average yearly sums of precipitation in the wheat-growing season on the farm over the last 10 years	1,071	109	1,060

(Continues)

TABLE 1 (Continued)

Variables	Type/Unit	Description	Mean	Std.Dev.	Median
Behavioral characteristics					
Exp yield decrease	Scale 1-5	Expected yield decrease in pesticide-free wheat production	3.1	1.4	3.0
		=1: none; =2: 0% – 5%; =3: 5% – 10%; =4: 10% – 15%; =5: > 15%			
Exp yield risk	Scale 1-4	Expected increase in years of crop failure or heavy yield losses	3.0	1.3	4.0
		=1: every 20 years; =4: every 5 years			
Risk preference	Scale 0-10	Willingness to take risks in plant protection =0: none; =10: very high	4.8	2.6	5.0
Pos environmental effect	Scale 1-5	Farmers' expectation that program participation has positive environmental effects	3.1	1.3	3.0
Openness innovation	Scale 1-5	Stated openness to agricultural innovations	3.3	1.1	3.0

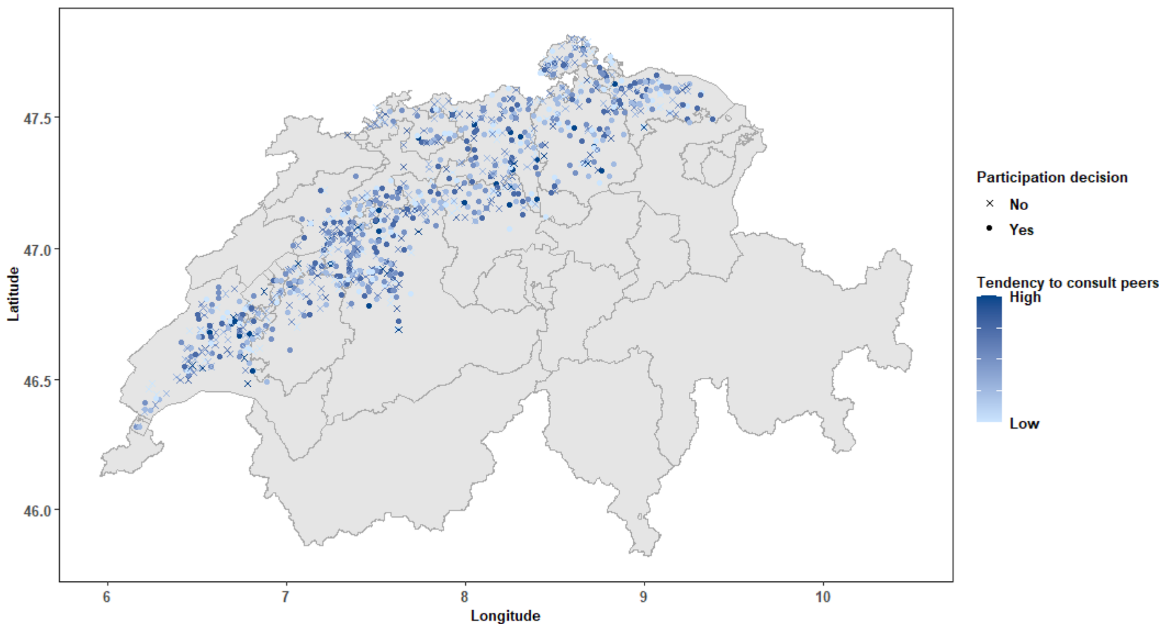

FIGURE 1 Farmers' adoption decision and tendency to consult peers in agricultural decisions

peer group is associated with .2 percentage point lower probability to adopt the program. While we expect farmers with peers willing to take risk in plant protection may be encouraged rather than discouraged to adopt the program, the negative effect of neighbors' risk preference may arise from prior negative experience in taking risks in plant protection. Nonetheless, the economic significance of the coefficient estimate of this variable is low. In model (4), a farmer with an additional peer having experience (or direct access to someone with experience, see footnote 3) in herbicide-free production is 1.2 percentage points more likely to adopt the program than those without experienced peers. This suggests that having access to peers' experience in relevant agricultural practices may facilitate a farmer's decision to adopt the innovative practice, in line with expectations.

TABLE 2 Estimated spillover and individual effects in pesticide-free wheat program adoption.

	Spatial proximity (1)	Spatial & information (2)	Spatial proximity (3)	Spatial & information (4)
Peer effects $(I-K)A\omega_k$				
Peer adoption	.113	.225***	.330*	.176***
	(0.123)	(0.070)	(0.188)	(0.065)
Contextual effects $(I-K)Cx_k^c$				
Age	.002	.001	−0.00001	−0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Education	−0.044	−0.064	−0.079	−0.061
	(0.119)	(0.117)	(0.111)	(0.108)
Agricultural land	.001	.001	.001	.001
	(0.002)	(0.002)	(0.001)	(0.001)
Wheat share	.305	.291	.302	.260
	(0.326)	(0.323)	(0.300)	(0.298)
Workforce	.028	.026	.018	.015
	(0.039)	(0.039)	(0.036)	(0.036)
Soil conservation	.031	.035	.059	.052
	(0.066)	(0.065)	(0.061)	(0.060)
Machine	.010	.014	−0.045	−0.005
	(0.081)	(0.076)	(0.078)	(0.073)
Experience	.090	.093	.109	.122*
	(0.072)	(0.071)	(0.067)	(0.066)
Exp yield decrease			−0.018	−0.021
			(0.023)	(0.023)
Exp yield risk			.009	−0.002
			(0.026)	(0.025)
Risk preference			−0.020*	−0.016
(plant protection)			(0.012)	(0.012)
Pos environmental effect			−0.019	.014
			(0.033)	(0.023)
Openness innovation			−0.026	−0.030
			(0.028)	(0.028)
Own characteristics $(I-K)x_k^c$				
Age	−0.002	−0.002	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Education	.088	.090	.053	.055
	(0.060)	(0.059)	(0.055)	(0.055)
Agricultural land	−0.002*	−0.002**	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Wheat share	−0.342**	−0.313*	−0.195	−0.163
	(0.162)	(0.161)	(0.149)	(0.149)
Workforce	.003	.005	.002	.004
	(0.017)	(0.017)	(0.016)	(0.016)
Soil conservation	−0.033	−0.040	−0.045	−0.047
	(0.034)	(0.034)	(0.032)	(0.031)
Machine	.166***	.174***	.075*	.084**
	(0.041)	(0.041)	(0.039)	(0.039)

(Continues)

TABLE 2 (Continued)

	Spatial proximity (1)	Spatial & information (2)	Spatial proximity (3)	Spatial & information (4)
Experience	.027	.020	−0.016	−0.015
	(0.037)	(0.037)	(0.035)	(0.034)
Exp yield decrease			.004	.003
			(0.012)	(0.012)
Exp yield risk			−0.061***	−0.061***
			(0.013)	(0.013)
Risk preference			.018***	.018***
(plant protection)			(0.006)	(0.006)
Pos environmental effect			.110***	.109***
			(0.012)	(0.012)
Openness innovation			.022	.021
			(0.014)	(0.014)
Observations	1,029	1,029	1,029	1,029
Adjusted R^2	.022	.032	.182	.185
F Statistic	1.780***	2.115***	6.707***	6.840***
Weak Instrument	1.523*	40.39***	2.638***	48.613***
Sargan Test	19.611	34.10	30.598	20.893
Residual Moran's I	.016	-0.0004	-0.002	.019

*, **, ***denote statistical significance at the 10%, 5%, and the 1% levels, respectively. Standard errors are in parentheses. *Machine = 1* if farmer has access to machinery for pesticide-free production; *Experience = 1* if farmer has prior experience with herbicide-free production; *Pos environmental effect* refers to farmer's expectation about the program's positive environmental effects; *Openness innovation* refers to farmer's openness to agricultural innovation. Coefficient estimates on land ownership, farm succession, share of off-farm income, language, municipality-level mean of delivered Extenso wheat quantities, share of organic farming, weed abundance, soil and slope suitability for wheat production, temperature, and precipitation are not reported in the table.

Comparing models with the two sets of covariates, with behavioral characteristics specific to the pesticide-free wheat program included, the magnitude of estimated peer effects in model (4) is lower than that in model (2). The magnitude and statistical significance of estimated coefficients on general farm and farmer characteristics (in the panel "Own characteristics") also reduce from models (1) and (2) to models (3) and (4). This indicates additional explanatory power from a richer set of relevant farmer characteristics in farmers' decision in adopting pesticide-free wheat production. In particular, the difference reaffirms the importance to account for farmer behavioral characteristics in assessing potential peer influence. While tendency to consult peers in agricultural decision-making is particularly related to the tendency of information exchange and therefore social interactions within a peer network, other characteristics may indirectly influence social interaction. In the robustness checks below, we further test the sensitivity of our results to the behavioral characteristics in the model.

In terms of farmers' own characteristics, estimates are qualitatively consistent across different specifications. As we discuss above, with farmer behavioral variables included in models (3) and (4), general farmer and farm characteristics bear less statistical significance or lower explanatory power compared to models (1) and (2). Since models (3) and (4) contain a similar set of covariates to the main model in Möhring and Finger (2022), we also compare estimates of farmers' own characteristics in these two models to those in Table 3 of Möhring and Finger (2022) for the common covariates. Different from Möhring and Finger (2022), we do not find a significant association between soil conservation and adoption of the pesticide-free production system. The difference could possibly be due to spatial patterns in soil conservation practices which are associated with the network fixed effects. As we discuss above, extension services (organized at the cantonal level) could influence farmers' choice of agricultural practices. Since we apply canton-level network fixed effects to address this issue, the variation in soil conservation across cantons could be absorbed by the fixed effects. Consistent with Möhring and Finger (2022), we find that higher expected yield risk is associated with lower probability of adoption, whereas access to machinery, willingness to take risk, and perception that the program has positive environmental impacts are associated with higher probability of adoption.

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Table 2 also presents results of diagnostic tests for the model specifications. First, we test whether the instrumental variables are weakly correlated with the endogenous peer adoption variable, which would bias the estimates of peer effects. Results show that for models (1) and (3) with social matrices defined only by spatial proximity, while the test statistics are statistically significant, the values are rather small, suggesting a potential weak instrument issue. For models (2) and (4), the test statistics are an order of magnitude larger, indicating a strong correlation between the instruments and peer adoption. Second, since we use more instrumental variables than the number of endogenous variable, we also apply the Sargan test, with the null hypothesis that the over-identifying restrictions are valid for the model. The insignificant test statistics indicate that the over-identifying restrictions are satisfied. Therefore, including more instruments than the number of endogenous variable in the model does not cause misspecification. Third, we calculated the Moran's I test statistic of the residuals of each model to test for spatial autocorrelation in the residuals. The insignificant test statistics indicate that by specifying peer effects and contextual effects, our model has sufficiently captured the spatial structure in the data.

To check the robustness of the main estimation results, we estimate models with alternative specifications in variable definition, social matrix definition, sample, model specification, and estimation methods, as discussed in the Empirical Strategy section. Estimates from the alternative specifications are largely consistent with the baseline estimation, though models with weights in the social matrix accounting for farmers' tendency to consult peers are more robust across specifications. We discuss detailed results of the robustness checks in the Appendix.

6.1 | Information link and peer effects on adoption

To further illustrate the implications of the estimated peer effects, we simulate the adoption of pesticide-free wheat production under two scenarios. These scenarios differ in whether policymakers take into account farmers' tendency to consult peers when targeting certain farmers to adopt the system. Our illustration is based on the canton of Bern, which represents the most important Swiss canton in terms of agricultural production in terms of number of farms. In our sample, there are 257 (of in total 1029) farms from the canton. At the baseline, that is, according to adoption information in the survey, there were 155 adopters and 102 non-adopters. Suppose that out of the 102 non-adopters, 20 are targeted by the policymaker to adopt the pesticide-free production system. We are interested in how the peer effects generated by the 20 additional adopters may change when the other non-adopters' tendency to consult peers are accounted for.

In our econometric analysis, we measure peer effects as the change in a farmer's probability to adopt due to a change in the number of adopting peers. The total peer effects due to the 20 new adopters is thus measured as the total increase in probability to adopt among the non-adopters who have the 20 new adopters in their peer network. We use the estimate of peer effects from model (4) in Table 2 to calculate the adoption outcome, that is, an additional adopter in a farmer's peer group would increase the farmer's probability to adopt by 1.8 percentage points. Since we are interested in how accounting for farmers' tendency to consult peers may affect peer effects in farmer networks, we hold all other covariates at their mean value. In other words, we hold constant the contextual effects of the additional adopters in the simulation.

In the first scenario, we assume that the 20 additional farmers are randomly selected by the policymaker. As we randomly draw 20 new adopters out of the 102 non-adopters, they turn out to be peers of 54 non-adopters. We then calculate how the new adopters influence the adoption probability of their non-adopter peers in the canton, which amounts to an increase in the summed adoption probability of the 54 non-adopters by 132 percentage points. Depending on the number of new-adopter peers for each non-adopter (1 to 3), the individual probability increase ranges from 1.8 to 5.4 percentage points.

In the alternative scenario, we assume that the policymaker does not target farmers randomly, but can focus on specific farmers. We assume they can first evaluate the social ties among farmers, then assign the new adopters in neighborhoods of non-adopters with the highest tendency to consult peers. For simplicity, we assume that the 20 new adopters again belong to peer networks of 54 non-adopters. Instead of a random draw, we assign them to the non-adopters with tendency to consult peers of value 5 (which comprises 6 non-adopters), 4 (17 non-adopters), or 3 (31 non-adopters). We further assume that the 6 non-adopters with the highest tendency to consult peers receive the highest number of new adopters in their peer network (three new-adopter peers), the 17 non-adopters with the next highest value receive new new-adopter peers, and the other 31 non-adopters each receive one new-adopter peer. Assigning new adopters to networks of high tendency to consult peers leads to an increase in the summed adoption probability of the 54 non-adopters by 175 percentage points, which is approximately 33% higher compared to the first scenario (random allocation). The individual level of probability increase ranges from 1.8 to 9 percentage points. Therefore, if policymakers target farmer networks of higher overall tendency to consult peers when they encourage new adopters, the multiplier effects among peer farmers can be considerably amplified, which would accelerate the diffusion process of the novel production system.

6.2 | Discussion

Overall, we find evidence of positive spillover effects in farmers' adoption decisions (i.e., peer effects), as well as spillover effects in farmers' willingness to take risk (negative) and prior experience in herbicide-free production (positive) in the adoption of pesticide-free wheat production (i.e., contextual effects). These spillover effects apply to both realized and intended adoption of the novel production system. These results provide empirical evidence of peer influence in adopting innovations for sustainable agriculture in a context with well-functioned extension services, institutional support, and a high-level of environmental awareness among farmers, such as in Europe. Across the two measures of social interactions within spatially defined farmer peer networks, estimates of peer effects from models accounting for farmers' tendency to consult peers are robust across model specifications and samples. These results reinforce contentions from previous studies in other contexts on the value of effective information links in assessing peer effects in farmer behavior (e.g., Conley & Udry, 2010; Genius et al., 2014; Läpple et al., 2017) and extend this literature by providing empirical evidence in the context of an input-reducing production system.

Our findings provide insights into pathways towards large-scale adoption of low-input agricultural innovations towards more sustainable farming practices. Even in countries such as Switzerland with broad availability of information for farmers, peer influence can play an important role in spreading innovations. In particular, consultation with the most communicative farmers and those with relevant experience in communities could support large-scale implementation of innovative practices. This is especially important in light of the major challenges faced by transforming agricultural systems on a large scale towards reducing environmental impacts and meeting growing demand for food. Our results show that spillover effects via effective information exchange among farmers can facilitate the diffusion of sustainable agricultural practices with innovations that lead to reduction in inputs harmful to the environment and human health. Our simulation further illustrates that when promoting innovative agricultural practices via targeting certain farmers to adopt, policymakers could leverage farmers' willingness to consult other farmers in order to maximize peer effects and accelerate the diffusion process.

Our analyses have several limitations. First, as we mention above, the innovative agricultural system we study is implemented in a developed country with strong institutional and technological infrastructure, and high educational level of farmers. Information availability may therefore be relatively high compared to countries without such endowments, and farmers may rely on their peer networks to a lesser extent when it comes to making agricultural decisions. As such, the estimated magnitude of peer effects should not be generalized to other contexts and rather constitutes a lower bound. Second, information exchange among farmers may go beyond spatial peer networks, especially in light of the advancements in digital communication methods. That is, farmers may belong to peer networks in multiple forms and dimensions of social ties. Nonetheless, despite these limitations, a key message our study communicates is that given a specific institutional context and type of peer network, it is crucial to account for variation in the level of effective information exchange across individual farmers when exploiting peer networks to promote innovation diffusion. Third, our analyses are based on information collected from a single survey wave. Peer effects may evolve over a longer period of peer learning or learning by doing from farmers' own experience, yet our data are not designed to study the learning process. Nonetheless, since the survey is conducted with wheat farmers within a long-established producer organization, the survey data still allow us to examine peer effects based on the existing information links.

7 | CONCLUSION

In this study we investigate spillover effects in the adoption of a novel large-scale pesticide-free wheat production system. Such production systems could be a major contributor to reaching policy goals on pesticide risk reduction and currently receive attention in large research and industry programs as well as from policymakers. Information on how to effectively and efficiently achieve large-scale adoption of such novel production programs will be key for their successful implementation in Europe and other regions.

We highlight the important role of farmer networks in farmers' adoption decisions of pesticide-free production and show how farmer networks and effective information exchange within such networks could facilitate the implementation and diffusion via spillover effects from both peer actions and peer characteristics. We refine social ties in spatially defined farmer networks with farmers' tendency to consult peers in agricultural decision-making. We therefore capture not only spatially mediated spillover effects, but also heterogeneous peer effects due to differences in the extent to which peer opinions are accounted for by farmers. The variability and asymmetry in the tendency to consult peers further provide important additional insights in how policymakers could exploit social links to promote innovation diffusion, which we further illustrate in a simulation.

Our findings have clear policy implications. We show that multiplier effects for the diffusion of agricultural innovations, such as the pesticide-free production system, hinge on effective information exchange among farmers. Creating peers with experiences on pesticide-free farming practices increases the probability of adoption also of others. This mechanism can be further improved in terms of efficacy and efficiency. From a practical perspective, we contend that policymakers or food value chain actors can increase effectiveness and efficiency of interventions supporting adoption by targeting farmers as new adopters in networks of stronger social ties, so as to leverage multiplier effects, rather than arbitrary targeting of farmers as new adopters. Knowledge of the strength of social ties in a given farmer network, for example, from extension specialists or producer organizations, could be particularly relevant. Such multiplier effects apply to both realized adoption and intended adoption, with the latter also relevant in the context of a newly developed novel production system.

Our analysis provides implications for further research. In light of the importance of effective information exchange in understanding peer effects in agricultural innovations, future research shall explore in more detail the potential role of specific communication channels among farmers that could trigger the adoption of more sustainable farming practices. Additional to traditional channels, especially social media and digital communication may play a vital role, which can go beyond the spatially defined peer networks, and therefore create channels to distinguish the effect of information unaffected by spatially correlated natural conditions. In a similar vein, it could be helpful to create novel channels for exchange of information among farmers to facilitate such diffusion, which is particularly relevant in regions where the spatial density of farmers is relatively low. In the context of pesticide-free production, the diffusion of the innovative production system can also teach us how to achieve pesticide reduction through coordination on a broader scale, for example, by managing pests at a landscape level via coordinating preventive efforts and crop rotations. Finally, the effects on innovation diffusion due to peer influence could be even more prominent in contexts where strong institution or policy support is lacking, for example, developing countries and subsistence agriculture. Therefore, research in other countries and contexts would provide additional insights in the role of effective information exchange and spillover effects among farmers.

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