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Rose Deperrois, Adélaïde Fadhuile, Julie Subervie

CEE-M

CENTER FOR ENVIRONMENTAL ECONOMICS - MONTPELLIER

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Social Learning for the Green Transition

Evidence from a Pesticide Reduction Policy

Rose Deperrois*[1,2], Adélaïde Fadhuile[2], and Julie Subervie[1]

[1]CEE-M, Univ. Montpellier, CNRS, INRAE, Institut Agro, 34060 Montpellier, France.
[2]GAEL, Univ. Grenoble Alpes, CNRS, INRAE, Grenoble INP, 38058 Grenoble, France.

Abstract

Social learning and the diffusion of innovations through peers are key components of agro-ecological transition, as they contribute to the generalization of good practices and improve the efficiency of public policies by increasing the number of farmers reached at no additional cost. We evaluated the spillover effects of a pesticide reduction scheme, implemented in France during the 2010s, which was designed to train farmers in pesticide-saving practices and encourage knowledge diffusion beyond the scope of enrolled farms. We estimated a fixed-effect model using pseudo-panel data collected at the national scale and found that doubling the share of enrolled farms within cohorts would reduce pesticide use by 7.3% to 10% on average. We found an additional effect of a similar magnitude when doubling the share of farms attending demonstration days hosted by farmers trained through the program, this impact being all the stronger as the share of enrolled farms is high. These results suggest that agricultural training programs with peer-sharing component are likely to generate spillover effects and increase the adoption of new practices at a lower cost than traditional programs.

Key Words: Agricultural Policy, Pesticide, Social Learning, Public Policy Evaluation.
JEL Codes: Q15; Q18; Q25; Q28; Q53.

*Corresponding author: rose.deperrois@inrae.fr, Institut Agro Batiment 26, 2 place Pierre Viala 34060 Montpellier, France

1 Introduction

Peer effects are a subject of increasing attention in many areas of economic research. Peer influence can create social multiplier effects whereby an initial investment targeting one small group can lead to broader impact, as individuals close to but outside of the target group are influenced by its actions. When it comes to the agricultural sector, the adoption of green technologies is a critical issue to achieving the green transition. The adoption of a new technique often requires specific technical assistance, which cannot easily be provided to all eligible farmers because of the high costs this would entail. In this context, observational learning can play a crucial role in the diffusion of new practices. The literature provides several examples of the diffusion of agricultural innovations through social networks and peer effects in developing countries (Conley and Udry, 2010; Benyishay and Mobarak, 2019; Caeiro, 2019). However, there are many reasons why social learning might not ultimately lead to changed behavior, particularly as it does not constrain adoption decisions. Moreover, it is often difficult to identify and measure social learning accurately. To our knowledge, there is no prior evidence of the diffusion of green practices through social learning in the context of developed countries, where promoting agro-ecological transition is particularly challenging for policymakers. We aim at filling this gap by evaluating the spillover effects of a program designed to train farmers in pesticide-saving practices and encourage knowledge diffusion beyond the scope of farms enrolled in the program.

The shift towards more sustainable farming practices has become a central issue of agricultural policy worldwide.[1] Water and soil pollution resulting from the extensive use of pesticides indeed poses a serious threat to biodiversity, as well as to the health of farmers and consumers, which became a cause of growing concern in public opinion.[2] In response to growing concern about the risks associated with pesticide use, the French government en-

[1]The European Commission made sustainable food production a priority of the European Green Deal, with ambitious targets set for Member States by the Farm-to-Fork strategy in 2020. Farm-to-Fork objectives include reducing the use and risk of chemical pesticide by 50% before 2030, and reducing by 50% the use of the most hazardous pesticides by 2030. More recently, the first European Nature Restoration Law was adopted in June 2022 by the European Commission, setting binding objectives to restore 80% of damaged European ecosystems and further restraining the use of pesticides in agriculture.

[2]See Beketov et al. (2013) for a review of the substantive biodiversity loss in Western European and Australian water streams due to contamination by pesticides; Sgolastra et al. (2020) for a specific review of the effect of neonicotinoid insecticides on bees; and INSERM (2021) for a comprehensive study of the impact of exposure to pesticides on human health.

acted a national plan in 2008, with the aim to reduce the use of pesticides by 50% overall by 2018. As part of this plan, 3,000 volunteer farmers were enrolled in a pilot program launched in 2012 – the DEPHY network – and were provided with free technical assistance in order to reduce pesticide use on their plot in a few years. Once trained, program beneficiaries had to organize visits and demonstration days on their farms, with the aim of passing on the knowledge accumulated during the program to neighboring farms that might be interested in adopting these new practices.

Monitoring data from farms enrolled in the program indicate that they indeed succeeded in significantly reducing their pesticide use in the space of a few years, contrary to other French farms that increased pesticide use on average. Two questions remain, however, regarding the additional effects of the program. Firstly, what role did the program play in the decrease of pesticide use, since those self-selected and motivated farmers would likely have decreased pesticide use without the help of the network? Secondly, was the "second-hand" training that visiting (also self-selected) farms benefited from sufficient to trigger a real change in their subsequent practices?

Our empirical analysis is built on repeated cross-sectional data about pesticide practices collected from a representative sample of around 28,000 plots in the arable field sector. We focus on arable crops, as they represent nearly 95% of France's utilized agricultural area. Following the approach first popularized by Deaton (1985), we constructed a pseudo-panel of 64 cohorts, using three essential criteria that impact a farmer's choice of agricultural practices: crop type, farm location and farm size. We then ran a fixed effects model regression to estimate the effects of the program on pesticide use in the 2014 and 2017 cohorts, keeping 2011 as the reference year. In doing so, we compared cohorts with varying proportions of participating and visiting farms, controlling for their time-invariant characteristics through fixed effects, as well as for a variety of time-varying confounding factors.

Our results point to a negative and significant impact of the training program on pesticide use among both enrolled and visiting farms. In particular, we found that doubling the proportion of enrolled farms in cohorts would reduce pesticide use by 7.3% to 10%, on average. In addition, we evaluated spillovers of the program on farms that reported having participated in visits to an enrolled farm and found again a significant decrease in pesticide use of a similar magnitude (while the share of visiting farms is higher than that of enrolled farms). This finding confirms the presence of knowledge spillovers in the vicinity of enrolled farms, which suggests that providing free technical assistance to peer networks can be effective in reducing pesticide use beyond the restricted circle of the primary beneficiaries of the program.

This result thus highlights the importance of social learning and the diffusion of knowledge to support agro-ecological transitions in developed countries.

We provide an overview of relevant studies in the literature on peer effects and the diffusion of agricultural practices through social learning in Section 2. We then present the empirical framework in Section 3. We provide estimation results along with a discussion of their interpretation in Section 4 and explore robustness checks in Section 5. Lastly, we discuss our results and conclude.

2 Conceptual Framework

The adoption pattern of new agricultural practices through the social networks of farmers has become an increasingly frequent topic in the literature in recent years. First introduced by Romer (1986) and Lucas (1988) as a factor of endogenous growth, social learning has been thoroughly studied in various microeconomics contexts. By social learning, we refer here to the diffusion of knowledge and practices through social interactions among economic agents. Social interactions are likely to affect individual behavior through observational learning, information transmission, a change of expectations or a change in social norms. Observational learning can reduce uncertainty and lead risk-averse agents to adopt new technologies more easily, while social pressure within groups of agents leads them to behave similarly. Manski (1993) identifies three mechanisms likely to drive social learning. Firstly, there are endogenous interactions, by which the individual's decision influences the decision of others and which is precisely what we seek to identify when we speak of peer effects. Then, there are contextual interactions, due to the fact that individuals have particular characteristics that can influence others' outcomes, and finally, there are correlated effects, due to the fact that individuals are subject to common constraints. The simultaneity of these effects introduces an identification issue for empirical studies of peer effects (the endogenous effect). When information about an individual reference group is available, this "reflection" problem can be solved by using a linear-in-means model (Manski, 1993; Bramoullé, Djebbari, and Fortin, 2009).

Other approaches have also been explored in the literature on social learning in agricultural contexts. For example, Foster and Rosenzweig (1995) provided empirical evidence of learning from peers in the context of the "Green Revolution" in India by exploiting aggregated data on the adoption of high-yielding seed varieties. More recently, field studies conducted at the individual level have provided detailed evidence of the diffusion of new technologies within farmer networks. Notably, Conley and Udry (2010) collected data about the people farmers know and talk to frequently in order to identify communication patterns in villages in Ghana. The endogeneity of social ties with regards to farming practices threatens the identification of peer effects, as farmers who have frequent interactions are likely to share some unobserved traits that influence their likelihood to adopt new technologies. The authors address this concern by exploiting the specific timing of pineapple planting to identify opportunities for information transmission regarding the shift to pineapple crops. Their results show that farmers are more likely to change their use of fertilizer after learning about the result of a similar change implemented by an "information neighbor", and that farmers have stronger responses in cases were the neighbor is an experienced farmer or a farmer with a similar income level.

The occurrence of social learning has also been documented through the implementation of Randomized Control Trials (RCTs). Benyishay and Mobarak (2019) found evidence of peer-to-peer learning in a study about technology adoption following a field experiment in Malawi. They show that assigning a peer farmer a "communicator" role to promote a new agricultural technology to other peer farmers is more efficient than when the knowledge is provided by a government-employed extension worker or a so-called "lead farmer". This result shows that farmers are most convinced by the advice of others who face agricultural conditions comparable to the conditions they face themselves (their peers), rather than more distant people in their village. The authors conclude that the social identity of the communicator influences others' learning and adoption of agricultural practices and that it is thus most efficient to design policies that provide incentives through peers.

In a large-scale study conducted in Western Kenya between 2010 and 2011, Chandrasekhar et al. (2022) found contrasting evidence on the adoption of different technologies within farmer communities. They randomly selected farmers to whom they distributed blue spoons designed to help the farmers measure the right amount of fertilizers to use on their plots and found that knowledge of the ownership of the blue spoons did spread through social networks of friends of the farmers that received them for free. However, interventions designed to encourage discussions about agricultural practices (cooperative meetings) and the distribution of coupons to encourage fertilizer purchase and therefore increase the value of communication about the blue spoons had no effect on the diffusion of the technology, whether among friends of the treated farmers or more broadly among the clusters that attended the same meetings. Findings reported an increase in the knowledge of the blue spoons among farmers in the same cluster as the treated farmers, but not an increased take-up of the technology. This suggests that the "subjective value" of knowledge differs based on the perceived reliability of the farmer spreading the information. These findings again highlight the importance of targeting the right individuals when trying to incentivize technology adoption through social learning among farmer networks.

The present paper studies potential knowledge diffusion in the context of pesticide reduction in French farming. While peer effects in the diffusion of agricultural technology are well documented in developing countries, the evidence in European contexts is much more scarce. Furthermore, the literature focuses on the diffusion of technologies that aim to improve productivity for the adopting farmers. When looking at environmental policies, the benefits of adoption are less clear, or at least not immediate, for farmers. We can therefore expect lower adoption rates in such contexts, although the learning mechanisms may well be similar to those described in the current literature. The drivers of adoption of conservation practices in agriculture, and more specifically the role of social norms and peer influence in driving adoption, have not yet been clearly measured (Yoder et al., 2019). In a recent study, Wang, Möhring, and Finger (2023) studied potential spillovers in the adoption of a pesticide-free wheat production system by looking at social ties among farmers in Switzerland. The authors exploit asymmetry in social ties to differentiate between Manski's peer effects and contextual effects and include a variety of controls in a cross-sectional regression to account for likely confounding effects. Their results suggest that experienced farmers facilitate the adoption of innovative practices more than inexperienced farmers, these effects being strengthened by peer effects. In the present paper, we tackle the identification issue quite differently, taking advantage of the panel structure of the dataset spanning from 2011 to 2017, where we directly observe the primary beneficiaries of the program (participating farms) as well as the indirect beneficiaries (visiting farms).

The French DEPHY network was designed to encourage social learning by placing participants in groups of ten to twelve peers supervised by an agricultural engineer.[3] In this context, the decisions of the individuals within each group may just as well be determined by a peer effect as by the influence of the engineer on each member of the group. However, the impact of demonstration visits on attendees can only be driven by the knowledge shared by DEPHY farmers during the event, as no other interventions confound this effect, and the attendees do not directly benefit from advice given by agricultural engineers. We use a quasi-experimental method to identify separately the direct (i.e., participating farms) and indirect (i.e., farms having attended a demonstration visit hosted by a DEPHY farm) effects

[3] A detailed description of the program can be found in Appendix A.

of the program on pesticide use. Our empirical strategy mimics a partial population design (Moffitt et al., 2001), where only a fraction of the total population of farmers is enrolled in the program and another fraction is exposed to spillovers through demonstration visits, while the remaining farmers are supposedly unaffected by the program. Such a design allows us to control for confounding factors that may drive outcomes of both participating and visiting farms.

3 Empirical Framework

First, we made use of repeated cross-sectional French survey data about agricultural practices, collected from a representative sample of farmers, to build a pseudo-panel of cohorts. We then ran a fixed-effect model using this pseudo-panel dataset to estimate the direct effect of the program, as well as spillover effects, on pesticide use across cohorts.

3.1 Data Sources

The French Ministry of Agriculture and Food regularly produces extensive surveys of agricultural practices, which are available upon the Ministry's authorization. The surveys cover representative plot samples for various types of crops, including field crops.[4] The most recent iterations of the agricultural practices survey for field crops were conducted in 2011 and 2017, with an additional intermediary survey conducted in 2014, specifically on phytosanitary practices. Our database therefore includes one observation prior to the start of the program (2011) and data on two years of practices during the program (2014 and 2017).

3.2 Outcome and Control Variables

We considered two measures of pesticide use: the Treatment Frequency Index (TFI) and the number of Application Rounds (APP). Both are included in our original data. The TFI was developed in the 1980s in Denmark and is now used worldwide, including by French policymakers as the main monitoring indicator of the French Ecophyto plan (Pingault et al., 2009). It captures the number of reference doses applied per hectare, taking into account the registered dosage for each product, as well as the Share of Treated Area (STA), i.e., the

[4] A detailed description of data sources is provided in the Appendix B.

surface to which the product is applied. In the surveys, the TFI is computed as follows:

$$TFI_i = \frac{AD_i}{RD_i} \times STA_i, \tag{1}$$

where i refers to the product, AD_i is the applied dose of product i, RD_i is its reference dose and STA_i the share of treated area, i.e., the area treated with chemicals expressed as a proportion of the utilized agricultural area. Based on this formula, the TFI is set to be equal to *one* when the product is applied, as defined in the reference dose, to the whole surface area of the plot. It thus gives a good indication of pesticide pressure.

For the purpose of the present analysis, we looked at the aggregated TFI, which captures the overall change of practices. More specifically, we focused on chemical TFI, excluding "low-risk pesticides" (according to a list of low-risk pesticides defined by the French Ministry of Agriculture and Food), since the DEPHY program promotes the adoption of these low-risk pesticides as an alternative to more dangerous products.

We then further break down the terms of Equation 1:

$$AD_i = D_i \times APP_i, \tag{2}$$

where D_i is the dose of active product in product i and APP_i the number of pesticide application rounds. We looked at the number of APP_i application rounds as an additional outcome to explore a potential channel that could drive TFI reduction. As the registered dose is fixed for a given period, a change of TFI_i over a given area without any change of APP_i would thus be attributed to a change of D_i, which we do not observe directly.

The surveys also includes some questions about labels and environmental schemes according to which each plot is cultivated, which we used to build control variables capturing other environmental commitments.

3.3 Treatment Variables

The 2014 and 2017 surveys provided us with two important pieces of information about the surveyed plot, namely, whether the farmer is a DEPHY program participant and whether he has already attended a demonstration visit offered by the DEPHY program. We thus built two binary treatment variables that measure direct and indirect program participation. The first level of treatment (hereafter T1) is DEPHY network membership, materialized by the agreement with the DEPHY terms of reference (the so-called *cahier des charges*). The 2017 agricultural practices questionnaire included a question about the respondent farm's commitment to DEPHY, which we used to identify direct program participants. For the year 2014, DEPHY participants were identified through data collected by the Ecophyto plan.[5] In our data, the treatment variable T1 equals one if the farmer was a member of the program in 2014 or 2017, and zero otherwise.

We investigated knowledge and information spillovers through the construction of another treatment variable, T2, taking the value of one for non-members who attended demonstration visits. We used the information collected during the 2014 and 2017 surveys to build T2. The two levels of treatment (T1 and T2) are mutually exclusive so that the same farm cannot be both a direct beneficiary and a visiting farm.

3.4 Construction of the Pseudo-panel Database

Deaton (1985) theorized the pseudo-panel approach as a way to aggregate observations into cohorts, with each cohort being representative of a segment of the population that can then be observed at different dates. The robustness of this approach has since been well established (Moffitt, 1993; Verbeek, 1996; Gardes et al., 2005). From the repeated cross-sections available for the years 2011, 2014 and 2017, we followed this approach to build cohorts along three defining criteria:

1. Farm location: six regions were defined according to their climatic and soil characteristics, see Figure C.3 in Appendix C.

2. Crop type: six types of crops, see Figure C.5 in Appendix C.

3. Utilized Agricultural Area (UAA): two groups were defined using a cutoff at 150ha, see Figure C.7 in Appendix C.

In theory, this procedure would generate 72 cohorts per year. In practice, however, as some categories were empty, we ended up with 64 cohorts in both 2011 and 2017 and 62 in 2014. The average cohort size was around 330 farms each year (Table 1). We explore the robustness of our results to an alternative pseudo-panel definition in Section 5.

[5] Agrosyst data accessed in May 2017.

Table 1: Cohort characteristics

	Number of farms	Number of cohorts	Average Cohort size	Cohort Size SE	Cohort Size Min	Cohort Size Max
2011	20,800	64	325	338.29	9	1,682
2014	20,646	62	333	293.27	27	1,603
2017	21,056	64	329	249.41	28	1,227

Note: SE, Min and Max stand for standard error, minimum and maximum value of the cohort size, respectively.

3.5 Model Specification and Estimator

Our main model specification is described in Equation 3:

$$Y_{ct} = \alpha + \beta_1 T1_{ct} + \beta_2 T2_{ct} + \mu_c + \nu_t + \gamma X_{ct} + \epsilon_{ct}, \tag{3}$$

where c denotes the cohort and t the year; μ_c and ν_t are, respectively, cohort and year fixed effects; X_{ct} is the vector of control variables, namely the share of organic farms and of farms enrolled in an agro-environmental scheme (AES) t the European Union's common agricultural policy (CAP) in the cohorts; α, β_1, β_2, γ are the parameters to be estimated, and ϵ_{ct} is the error term. The value of outcome Y_{ct} is the average of the individual levels within the cohort c at time t. We computed the share of treated individuals within each cohort in the same way. The two treatment variables are therefore defined as the share of participating farms (T1) and the share of visiting farms (T2) within each cohort each year. Both treatment variables are set to 0 in 2011, as enrollment in the program effectively began in 2012.

We also ran a specification that includes time-by-treatment interactions in Equation 4:

$$Y_{ct} = \alpha + \beta_1 T1_{ct} \times Year_t + \beta_2 T2_{ct} \times Year_t + \mu_c + \nu_t + \gamma X_{ct} + \epsilon_{ct}, \tag{4}$$

Finally, we further explored the cross-effects of T1 and T2 by estimating Equation 5. This allowed us to check whether the level of T1 influences the impact of T2; that is, if having a larger share of participating farms in the cohort increases the impact of demonstration visits – which could happen, for example, if neighboring farms could visit two DEPHY farms rather than one alone because of their high concentration:

$$Y_{ct} = \alpha + \beta_1 T1_{ct} + \beta_2 T2_{ct} + \beta_3 T1_{ct} \times T2_{ct} + \mu_c + \nu_t + \gamma X_{ct} + \epsilon_{ct}. \tag{5}$$

4 Results

4.1 Descriptive Statistics

This section briefly presents the main characteristics of the farms included in the initial sample and the main characteristics of the cohorts constructed by aggregating the farms.

Farm Data

The main characteristics of the plots used to construct the cohorts are presented in Table 2. We exclude meadows and mixed crops from the data, as they are not represented in each round of the survey and keep around 20,000 crops in the sample each year. The average overall Utilized Agricultural Area (UAA) increased over the period to 145 hectares in 2017, and the average plot surface increased to seven hectares. The APP remained stable, around five per year, and the TFI for all chemical pesticides increased over the period, from three to four, on average. The share of organic plots increased between 2011 and 2014 and remained stable between 2014 and 2017. Lastly, the share of farms that joined the DEPHY program increased over time (1% in 2014 and 2% in 2017) as well as did the share of visiting farms (6% in 2014 and 7% in 2017). In 2014, 110 DEPHY farms were surveyed, and 431 were surveyed in 2017 (of 1,450 DEPHY field crop farms enrolled in the program at this stage).

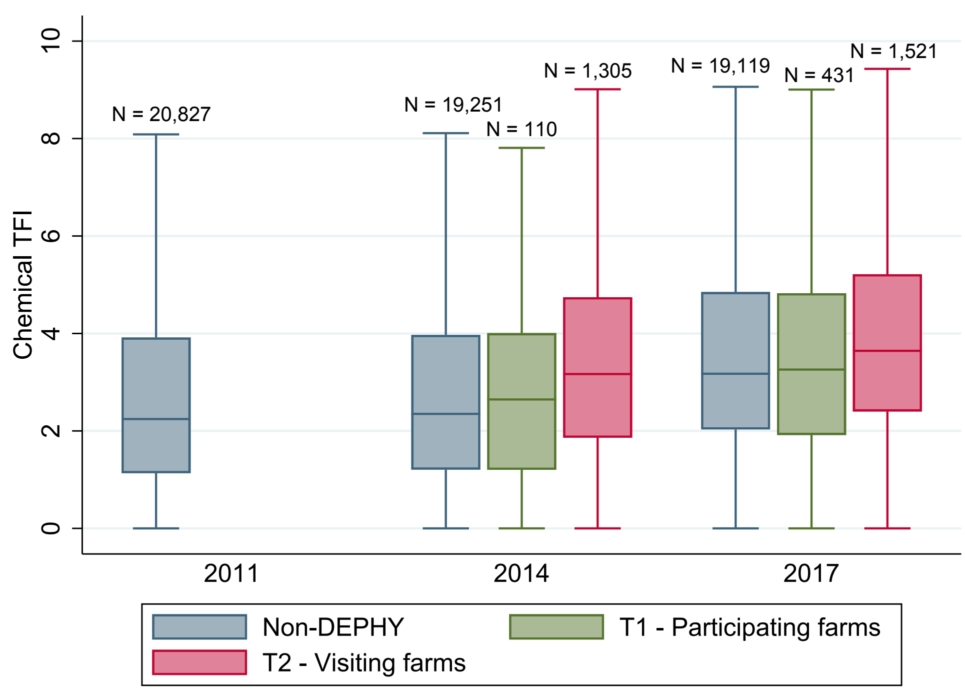
The distribution of chemical TFI among DEPHY farms (whether participating or visiting) in 2014 and 2017 is displayed in Figure 1. Quite surprisingly, DEPHY farms are not characterized by lower TFI in either of the two years, whereas one might have expected that the first farms enrolled would also be those whose efforts to reduce the use of pesticides would be the lowest. This finding is however consistent with the program's stated strategy not to recruit farms that were already performing better than the rest of French farms in terms of pesticide use.

Table 2: Farm characteristics

	2011		2014		2017	
	Mean	SE	Mean	SE	Mean	SE
UAA (ha)	120.66	90.30	134.40	99.07	145.85	97.76
Plot surface (ha)	4.13	5.13	6.66	6.77	7.13	7.08
APP	5.12	5.16	5.62	5.69	4.95	4.69
TFI	2.99	3.04	3.15	3.32	3.92	3.37
Organic farming = 1	0.05	0.22	0.06	0.24	0.06	0.23
AES = 1	0.02	0.14	0.06	0.24	0.05	0.21
T1. Participating farm = 1	0	0	0.01	0.07	0.02	0.14
T2. Visiting farm = 1	0	0	0.06	0.24	0.07	0.26
Observations	20,827		20,666		21,071	

Note: AES, Organic farming, AES, T1 and T2 are binary variables. Their mean value is the share of observations equal to *one* in the sample. SE stands for standard error.

Figure 1: Distribution of chemical TFI for DEPHY vs. non-DEPHY farms, 2011 to 2017



Note: Color should be used in print.

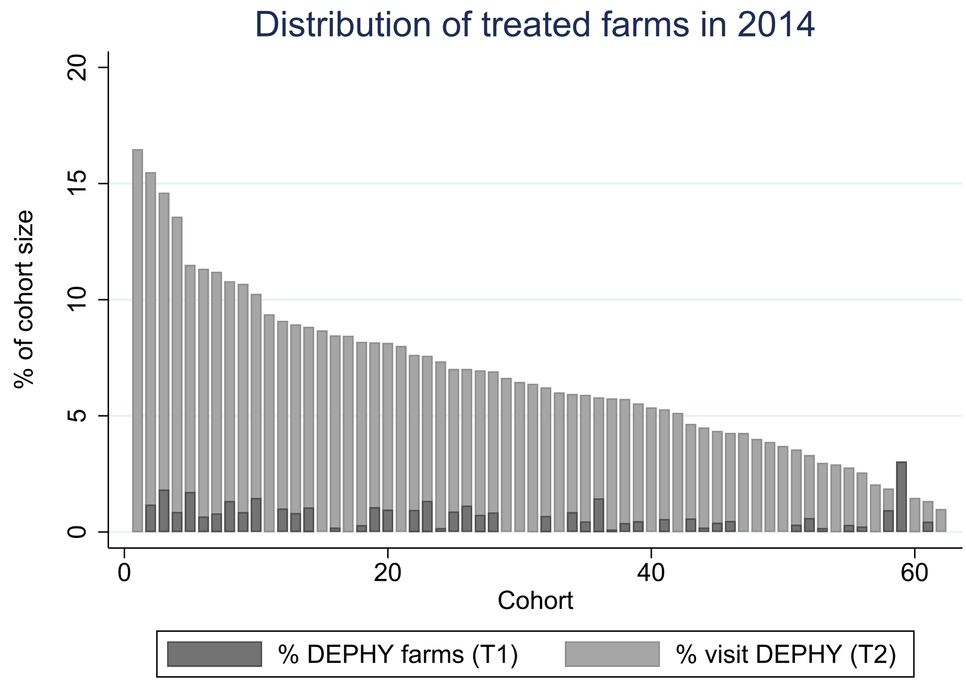
Cohort Data

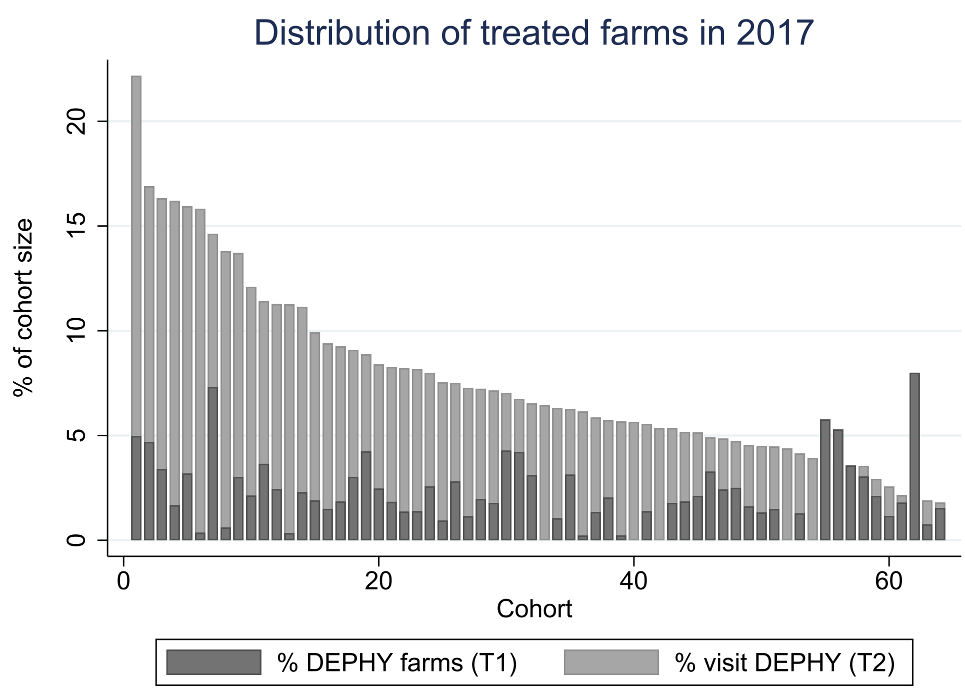
The distribution of treated farms within the cohorts is displayed in Figure 2, with summary statistics presented in Table 3. The share of participating farms ($T1 = 1$) ranges from 0% to 3.03% in 2014, and from 0% to 8% in 2017. The share of visiting farms ($T2 = 1$) is always greater than 0 in all cohorts, as it ranges from 0.99% to 16.48% in 2014 and from 1.80% to 22.17% in 2017. Figure 3 shows that the share of participating and visiting farms in each cohort does not appear to be strongly correlated, which suggests that the share of participating farms may not determine the intensity of spillovers in a given cohort. Additional descriptive statistics about the cohorts are provided in Appendix C (Figures C.4, C.6 and C.8), illustrating the distribution of treated farms depending on cohort construction criteria.

Table 3: Share of treated farms in the cohorts

	2014	**2017**
Participating farms: $T1 = 1$		
Average share (%)	0.56	2.26
(Standard error)	(0.59)	(1.67)
[Minimum;Maximum]	[0.00;3.03]	[0.00;8.00]
Visiting farms: $T2 = 1$		
Average share (%)	6.67	7.67
(Standard error)	(3.49)	(4.32)
[Minimum;Maximum]	[0.99;16.48]	[1.80;22.17]

Figure 2: Share of treated farms in each cohort





Note: For readability purposes, cohorts are ranked based on the share of visiting farms ($T2 = 1$). Note that the order is not the same from one year to another.

4.2 Estimation Results

Following Bellemare and Wichman (2020), we applied an Inverse Hyperbolic Sine (IHS) transformation in order to compute elasticities and account for the high number of zeros in our data. This transformation also reduces the impact of outliers and heteroskedasticity, if any, on estimation results. As a result, the estimated coefficient of the treatment variable can be interpreted here as the effect on the outcome of a 1% increase in the share of treated farms in the cohort. We also followed Gardes et al. (2005), who investigated the potential heteroskedasticity issue caused by the aggregation of data into cohorts of different sizes and brought to light the necessity of using robust standard errors in regression models, which we applied throughout the analysis.

Table 4: Direct and spillover effects on pesticide use (Equations 3 and 4)

	(1) TFI	(2) TFI	(3) APP	(4) APP
T1	-0.0621***		0.0256	
	(0.0190)		(0.0208)	
T2	-0.0540**		-0.0487*	
	(0.0236)		(0.0288)	
T1 × 2014		-0.0472		0.0065
		(0.0320)		(0.0378)
T1 × 2017		-0.0729***		0.0300
		(0.0239)		(0.0274)
T2 × 2014		-0.0171		0.0001
		(0.0259)		(0.0301)
T2 × 2017		-0.1016***		-0.1016***
		(0.0277)		(0.0328)
Constant	1.8427***	1.8527***	2.3463***	2.3546***
	(0.0277)	(0.0280)	(0.0308)	(0.0298)
Organic label	Yes	Yes	Yes	Yes
AES	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
N	190	190	190	190

Notes: TFI refers to the Treatment Frequency Index. APP refers to the number of application rounds. T1 is the share of participating farms in the cohort and T2 is the share of visiting farms in the cohort. All variables are in IHS. Reference year is 2011. Robust standard errors at the cohort level in parenthesis. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Impact of Participating Farms (Direct Effect)

Results of the estimation of Equations 3 and 4 are presented in Table 4. Column 1 shows that the marginal effect of increasing the proportion of T1 on the average chemical TFI of the cohorts is negative and significant at the 1% level. When looking at the year by year effect (Column 2), it is only significant in 2017. This suggests that the program would not have had any discernible effect in 2014, two years after its official launch. The magnitude of the coefficient in 2017 is roughly 0.073, meaning that increasing the share of T1 farms by 1% is associated with a 0.073% average decrease of TFI in the cohorts. Put differently, doubling the share of T1 farms in the cohorts (i.e., increasing it by 100%) would imply a 7.3% reduction of TFI, on average, within the cohorts.

The effects on APP are not significant regardless of the year (Columns 3 and 4). This suggests that the underlying mechanism behind the decrease in TFI is not driven by a change in the number of pesticide applications (APP). Therefore, it appears that the impact of the DEPHY network on pesticide use is mostly driven by a change in the doses of pesticides applied by enrolled farmers.

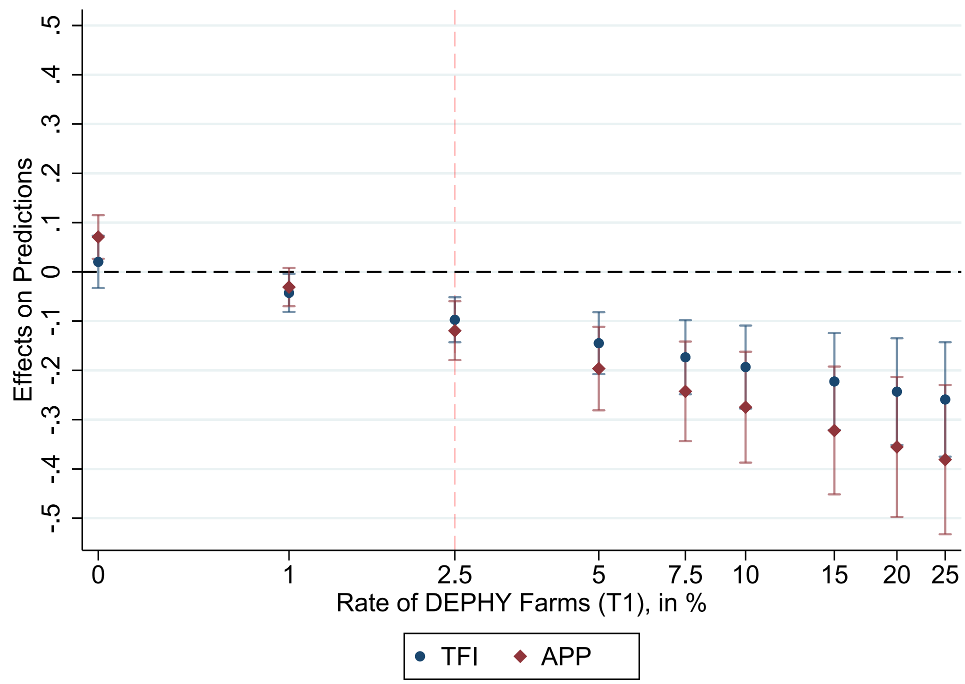
Impact of Visiting Farms (Spillover Effect)

Table 4 also reports a significant negative effect of increasing the share of T2 on the average TFI of the cohorts (Column 1). Similar to the impact of T1, the year by year interaction shows that the impact of visits during demonstration days became clearly established after the program had been implemented for some years (Column 2). The magnitude of the effect is similar to that of T1: it is slightly higher than -0.1, meaning that doubling the share of T2 farms would lead to a 10% decrease of TFI within the cohorts.

Interestingly, the coefficient associated with the impact of T2 on application rounds between 2014 and 2017 is significantly negative, while the effect of T1 on this outcome during the same period is indistinguishable from zero (Columns 3 and 4). While this could suggest that T2 farms reduce pesticide use through channels other than T1 farms, it is more likely that the effect on treatment frequency is estimated more precisely for T2 farms than for T1 farms. Indeed, T2 farms represent a larger share of the cohorts than do T1 farms, and their effect is estimated more precisely. This would imply that the lack of effect on the number of application rounds we observe for T1 farms is due to a lack of precision in our data, rather to an actual lack of impact.

We then looked at the cross-effects of T1 and T2 as described in Equation 5. The marginal effect of T2 estimated at various levels of T1 is displayed in Figure 3, and Table D.2 in Appendix D provides overall estimation results. When estimated at the average level of T1 in 2017, the effect of T2 on both the TFI and the number of application rounds is negative and significant. Overall, Figure 3 shows that the higher the T1 in the cohorts, the more pronounced the impact of T2 on average pesticide use. Note, however, that this relationship is not linear, since we applied an IHS transformation to the variables. Thus, the marginal effect of T2 when T1 is equal to 10% is roughly 0.24, meaning that for this level of T1, doubling T2 would lead to a TFI reduction of about 24%. For T1 equal to 20% of the population, this suggests that doubling the share of T2 farms would lead to a TFI reduction of about 30% only.

Figure 3: Marginal impact of T2 at various levels of T1 (Equation 5)



Note: The dotted red line illustrates the average share of T1 in the 2017 cohorts. Estimated effects are computed from Table D.2 for the two outcomes: TFI (Treatment Frequency Index) and APP (number of application rounds). The segments represent the 95% CI. The point estimates were computed from $\beta_2 T2_{ct} + \beta_3 T1_{ct} \times T2_{ct}$ in Equation 5.

5 Discussion and Robustness Checks

5.1 Parallel Trends Assumption

Our identification strategy relies on the fact that, after controlling for the share of organic farms and farms enrolled in an AES, cohorts with different shares of T1 and T2 would have followed a parallel trend with regards to pesticide use in the absence of the program (the parallel trend assumption). We tested this assumption by looking at the impact of increasing the shares of T1 and T2 on cohort pesticide use in 2014, a year during which we do not expect to detect any effect of the program, knowing that it only started a few months ago. Any effect observed in 2014 would then be likely due to the underlying differences of cohorts with a high share of treated farms rather than to the true impact of the program. Results rather show a lack of effect of the program in 2014. They are reported in Columns 2 and 4 of Table 4, suggesting that our estimation strategy performed well.

5.2 Small Cohorts

Another concern with our identification is that, while the average cohort size for both years is high enough to ensure that the average outcomes within cohorts are representative of the true population, some cohorts are constructed based on a small number of observations. This can bias our results if this small cohort size is the result of the sampling design and the cohorts are not representative of the true population defined along the three criteria. However, a small cohort size can also simply be due to the small number of farms fitting into the given intersection of the three criteria in the population. In this case, the small cohorts are representative of an actual small part of the agricultural population and give an accurate representation of its practices. Upon investigation of the detailed characteristics of these small cohorts, we chose to include them in the main estimations and exclude them as a robustness check.

We found five distinct small cohorts in our sample. As cohort size varies throughout the years, some cohorts have fewer than 50 observations in some years and not others, while other cohorts are small in multiple years of our pseudo-panel. In total, they amount to ten observations, which are presented in Table 5. We reran the same estimations after excluding them from the sample. Results are reported in Table 6 below. The marginal impact of T1 on TFI increases in magnitude once small cohorts are excluded from the data, while the magnitude of the marginal impact of T2 decreases. Overall, these findings remain consistent with results obtained from the full dataset, suggesting that the inclusion of small cohorts does not significantly confound our findings.

Table 5: Small cohorts ($n \leq 50$)

	Number of occurrences
C-E Potatoes 150+ha	1
N-E Potatoes 0-150ha	2
S-E Industrial crops 150+ha	3
S-E Protein crops 150+ha	2
W Potatoes 150+ha	2
Total	10

Table 6: Direct and spillover effects on pesticide use without small cohorts (Equations 3 and 4)

	(1) TFI	(2) TFI	(3) APP	(4) APP
T1	-0.0788***		0.0004	
	(0.0225)		(0.0208)	
T2	-0.0401		-0.0203	
	(0.0243)		(0.0255)	
T1 × 2014		-0.0304		0.0106
		(0.0300)		(0.0363)
T1 × 2017		-0.1009***		-0.0020
		(0.0229)		(0.0209)
T2 × 2014		-0.0166		0.0100
		(0.0251)		(0.0304)
T2 × 2017		-0.0845***		-0.0666**
		(0.0287)		(0.0274)
Constant	1.8255***	1.8375***	2.3646***	2.3711***
	(0.0314)	(0.0318)	(0.0280)	(0.0281)
Organic label	Yes	Yes	Yes	Yes
AES	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
N	180	180	180	180

Notes: TFI refers to the Treatment Frequency Index. APP refers to the number of application rounds. T1 is the share of participating farms in the cohort and T2 is the share of visiting farms in the cohort. All variables are in IHS. Reference year is 2011. Robust standard errors at the cohort level in parenthesis. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

5.3 Alternative Pseudo-Panel Construction

As our identification strategy mainly relies on cohort level fixed effects to control for the endogeneity of the DEPHY network, it is crucial that cohorts effectively represent a stable portion of the population over the six years of our study. While the farms defined at the intersection of our geographical and crop type criteria likely remain similar over time, average farm size (as captured by total UUA) increased over the period. It is possible that the population of small farms as defined in 2011 differs from that of 2017, as the farms that remain small can have specific attributes distinguishing them from the others. We test the sensitivity of our results to an alternative pseudo-panel definition in which we define two cutoffs for farm size at 100ha and 200ha, thus creating three groups (compared to our previous cutoff at 150ha defining two groups). Characteristics of the new cohorts are displayed in Tables 7 and 8. The number of cohorts respectively increases by 32, 31 and 32 for each year, compared to our original pseudo-panel with a lower average cohort size. The distribution of T1 and T2 farms in the new cohorts also differs in this new pseudo-panel, which has similar average values but broader ranges.

We tested the robustness of our results to this new pseudo-panel definition by estimating Equations 3 and 4 on the subsequent dataset. As the number of cohorts increased with our new pseudo-panel construction, so did the number of small cohorts (36 compared to ten in the initial pseudo-panel). Therefore, they are more likely to confound the results of this new estimation, and we reported estimation results both including small cohorts (Table 9) and excluding them (Table 10). The estimated impact of T1 on TFI remains stable in both estimations, but the impact of T2 is only significant when excluding small cohorts.

Table 7: Cohort characteristics for each year, alternative pseudo-panel construction

	Number of Farms	Number of Cohorts	Average Cohort Size	Cohort Size SE	Cohort Size Min	Cohort Size Max
2011	20,800	96	217	226.86	5	1189
2014	20,646	93	222	204.71	12	1152
2017	21,056	96	219	168.89	15	775

Note: SE, Min and Max stand for standard error, minimum and maximum value of the cohort size.

Table 8: Share of treated farms in the cohorts, alternative pseudo-panel

	2014	**2017**
Participating farms: $T1 = 1$		
Average share (%)	0.60	2.16
(Standard error)	(0.77)	(1.80)
[Minimum;Maximum]	[0.00;4.11]	[0.00;8.54]
Visiting farms: $T2 = 1$		
Average share (%)	6.64	7.55
(Standard error)	(3.80)	(4.66)
[Minimum;Maximum]	[0.00;17.01]	[0;27.80]

Table 9: Pseudo panel regression of pesticide use on T1 and T2, year by year - Alternative pseudo-panel construction

	(1) TFI	(2) TFI	(3) APP	(4) APP
T1	-0.0605***		0.0145	
	(0.0181)		(0.0184)	
T2	-0.0167		-0.0194	
	(0.0270)		(0.0230)	
T1 × 2014		-0.0062		0.0389
		(0.0304)		(0.0314)
T1 × 2017		-0.0830***		0.0063
		(0.0186)		(0.0210)
T2 × 2014		0.0032		0.0111
		(0.0282)		(0.0264)
T2 × 2017		-0.0490		-0.0566**
		(0.0327)		(0.0264)
Constant	1.8569***	1.8645***	2.3533***	2.3594***
	(0.0247)	(0.0235)	(0.0234)	(0.0225)
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Organic label	Yes	Yes	Yes	Yes
AES	Yes	Yes	Yes	Yes
N	285	285	285	285

Table 10: Pseudo panel regression of pesticide use on T1 and T2, year by year - Alternative pseudo-panel construction, no small cohorts

	(1)	(2)	(3)	(4)
	TFI	TFI	APP	APP
T1	-0.0708***		0.0050	
	(0.0145)		(0.0169)	
T2	-0.0268		-0.0140	
	(0.0193)		(0.0209)	
T1 × 2014		-0.0157		0.0136
		(0.0219)		(0.0204)
T1 × 2017		-0.0972***		0.0034
		(0.0145)		(0.0202)
T2 × 2014		-0.0111		0.0142
		(0.0229)		(0.0217)
T2 × 2017		-0.0620***		-0.0494**
		(0.0211)		(0.0241)
Constant	1.8257***	1.8339***	2.3596***	2.3652***
	(0.0209)	(0.0224)	(0.0180)	(0.0189)
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Organic label	Yes	Yes	Yes	Yes
AES	Yes	Yes	Yes	Yes
N	249	249	249	249

5.4 Replication on Vineyards

One limitation of the pseudo-panel analysis is that it cannot give the impact of the program on the use of pesticides in the enrolled or visiting farms themselves but only on the average practices within representative cohorts, which include both treated and untreated farms. To overcome this shortcoming and to complete our analysis, we used panel data collected from a representative sample of around 4,000 French vineyards. Vineyards represent less than 3% of the agricultural area of the country, but are the largest consumers of pesticides. We estimated a fixed-effect model using pesticide use data collected in 2010, 2013, and 2016.

These survey data do not make it possible to identify the farms enrolled in the program (T1), only those having taken part in a demonstration visit (T2). We therefore estimated the following models:

$$Y_{it} = \alpha + \beta T2_{it} + \mu_i + \nu_t + \gamma X_{it} + \epsilon_{it}, \tag{6}$$

$$Y_{it} = \alpha + \beta_1 T2_{it} + \beta_2 T2_{it} \times Year_t + \mu_i + \nu_t + \gamma X_{it} + \epsilon_{it}. \tag{7}$$

where T2 takes on the value of one when the farmer participated in a demonstration day, and zero elsewhere. Results are presented in Table 11. Column (1) reports a negative and significant effect of T2 on chemical TFI, which supports the results we got using pseudo-panel data collected from field crops. Column (2) moreover shows that this effect became apparent as early as 2013. This contrasts with our findings on field crop farming, where the impact of the program cannot be estimated with precision before 2017. Here, the effect can be interpreted directly at the individual level: attending a demonstration day organized by an enrolled vineyard reduces chemical TFI by approximately 0.4 points. On the other hand, the impact on the number of application rounds is not statistically conclusive, which suggests that improvements in the TFI are driven by the surface on which the pesticides are applied, rather than by the frequency of applications (Lapierre, Sauquet, and Subervie, 2019).

Table 11: Spillover effects on pesticide use, using vineyard surveys

	(1)	(2)	(3)	(4)
	TFI	TFI	APP	APP
T2	-0.4164***		-0.0934	
	(0.1399)		(0.2078)	
T2 × 2013		-0.4274**		-0.4905**
		(0.1835)		(0.2311)
T2 × 2016		-0.4061**		0.2791
		(0.1967)		(0.3072)
Constant	12.3443***	12.3443***	16.3332***	16.3330***
	(0.0435)	(0.0435)	(0.0649)	(0.0649)
Organic label	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
N	12,171	12,171	12,171	12,171

Notes: TFI refers to the Treatment Frequency Index. APP refers to the number of application rounds. T2 takes on the value of one for visiting farms and zero for others. Reference year is 2010. Robust standard errors in parenthesis. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

6 Conclusion

We explored the effects of the DEPHY network on pesticide use in field crop farming and found conclusive evidence of its impact on chemical TFI. Our results show that doubling the share of farms enrolled in the DEPHY network would reduce chemical TFI by 7.3% to 10%, on average. This result suggests that providing technical assistance to peer networks can be effective in significantly reducing pesticide use, which is a key finding for future agro-ecological policies.

Moreover, we found that the impact of the DEPHY program is not limited solely to members of the network: non-members that report having attended a visit or a demonstration held at a participating farm also changed their pest management practices. Indeed, our analysis shows that the marginal effect on chemical TFI of increasing the share of farms participating in such DEPHY events is negative and significant. The magnitude of the effect is similar to that of being directly enrolled in the program: without increasing the number of farmers enrolled, doubling the number of visiting farms would reduce chemical TFI by 10%, on average. The effect grows larger as the share of DEPHY farms increases. This finding is in line with the literature on peer effects and social spillovers in agriculture in developing countries. It suggests that investing resources to assist the transition of some farmers to more ecological practices can have repercussions throughout their communities and contribute to a broader change of practices on a larger scale.

The main contribution of this paper to the economic literature on agricultural practices and social learning is to showcase evidence of the direct and indirect impacts of a peer network program that provides technological assistance on agricultural practices. Future research could focus on building a measure of spatial spillovers and further explore their impact on pesticide use, following the approach developed by Missirian (2020). Another possible follow-up to this research would be to measure other forms of social spillovers by looking at farms that share a membership to a cooperative agricultural structure with a participating farm, for instance. This would provide a way to identify farmers that regularly interact with DEPHY members and then question whether or not these interactions lead to a change in pest management practices.

In terms of policy recommendations, this paper confirms the validity of the rationale behind the implementation of the DEPHY network and provides support for the extension of both the number of farms directly involved in the network and the number of farms reached through demonstration days. This is encouraging for the future of agro-ecological policies and in line with recent developments of the Ecophyto Plan, which has set the goal in 2019 to expand the DEPHY network from 3,000 to 30,000 farms. The objective of these "30,000 Ecophyto groups" is to expand the outcomes of the DEPHY network to a larger scale and continue to work on innovative and sustainable ways to reduce reliance on chemical pesticides in French agriculture.

Acknowledgements

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Data reference:
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Enquête PKGC 2011 (https://doi.org/10.34724/CASD.56.310.V1)
Enquête PhytoViti 2016 (https://doi.org/10.34724/CASD.43.2609.V2)
Enquête PKViti 2013-2014 (https://doi.org/10.34724/CASD.65.1206.V3)
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A Appendix A: The DEPHY Network

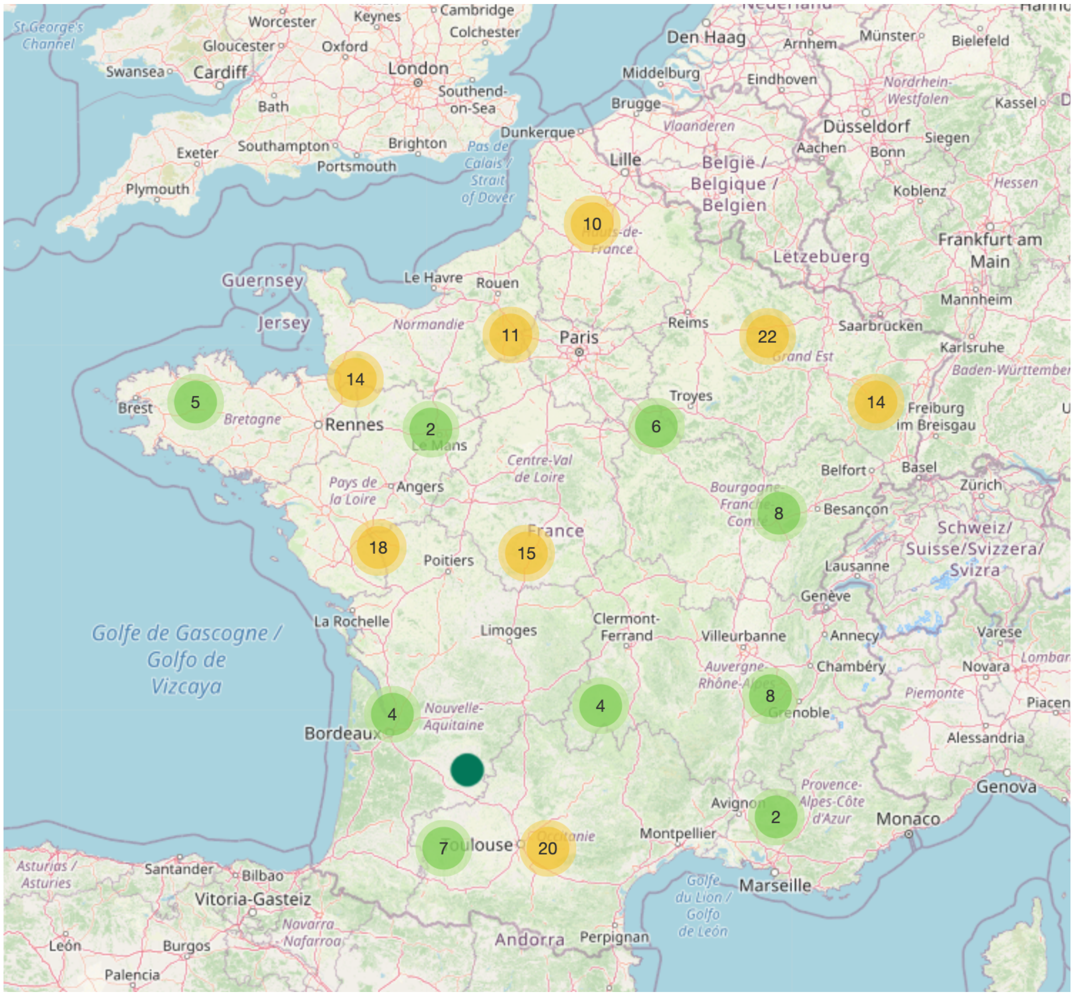
Since 2012, the French Ecophyto plan has financed the DEPHY (Demonstrate, Experiment and Produce references on low pHYtosanitary systems) program, a national peer-network of 3,000 farms committed to reducing pesticide use with the technical help of trained advisors. Member farms voluntarily joined the program between 2011 and 2016 and share the same goal of reducing pesticide use and experimenting with various methods to find alternative pest management techniques. Member farms share their good practices through technical leaflets openly available online, demonstrations held at their farms, educational videos and presentations at regional and national events. The network covers the main types of crops cultivated throughout France (arboriculture, vegetable crops, tropical crops, horticulture, field crops – polyculture and breeding, viticulture). The success of the program rests on farmers' willingness to implement innovative pest management strategies. The program aims to provide relevant advice to farmers in order to aide their transition away from pesticide use and also relies on its networking aspect to foster peer-to-peer learning within the DEPHY groups. The program only offers free technical assistance, no financial support.

The program's monitoring data points to an overall reduction of pesticide use by DEPHY members since joining the network.[6] However, this is not sufficient evidence to judge the impact of the program, as the choice to join the network is likely driven by intrinsic motivation to shift towards more eco-friendly agricultural practices, and the pesticide reduction observed in the network could be the result of members' initial drive to change their production systems in favor of more sustainable ones. The methodological challenge for the evaluator therefore consists in implementing an identification strategy that makes it possible to distinguish the effects of enrolling some specific farms from the effects of the program itself.

The distribution of the DEPHY field crop groups – polyculture and breeding – throughout France is displayed in Figure A.1.

[6] Reports published on the Ecophyto website show a decrease in the use of pesticides for network members: https://ecophytopic.fr/sites/default/files/2021-06/Evolution_IFT_DEPHY_FERME_2019_VF.pdf

Figure A.1: Map of the 133 DEPHY field crop groups (polyculture and breeding), 2022



Source: Ecophytopic website

Another key component of the DEPHY network is its contribution to knowledge production through openly accessible reports on the techniques used within the network. The program also organizes national and regional events, as well as visits to successful DEPHY farms, to promote good practices for pesticide reduction. One can therefore expect DEPHY to have impacts on farms that are not enrolled in the program but that use resources produced by the network to reduce their own reliance on pesticides. Further, DEPHY farms are supposed to serve as examples and promote environmentally-friendly practices to their peers through informal channels. Therefore, one can also expect that the network generated peer effects that encouraged non-member farms located near DEPHY farms to change their agricultural practices as a result of interacting informally with the direct program beneficiaries.

These spillovers are particularly relevant from a policy perspective, as they can potentially multiply the impact of the program for little to no additional cost.

B Appendix B: Data Description

The sampling procedure follows two steps. First, field crop farms are stratified depending on three criteria: i) whether they practice organic farming; ii) their location (at the department level for non-organic farms and at the regional level for organic farms); and iii) the total cultivated area of the farm. Next, farms are randomly selected within each strata, and plots are randomly selected among these farms. The number of farms and plots selected per strata is calculated based on the relative importance of each strata in the national distribution of farms. The selected plots can be re-weighted to extrapolate characteristics and draw conclusions at the national scale.

Table B.1: Characteristics of farm practice surveys

Survey year	Number of plots	Extrapolated surface (% of total crop surface)	Crop species covered
2011	25,420	90%	Soft wheat, hard wheat, barley, triticale, rapeseed, sunflower, protein peas , fodder corn, grain corn, sugar beet, potato, sugar cane temporary meadow, permanent meadow
2014 (reduced survey)	21, 054	90%	Soft wheat, hard wheat, barley, triticale, rapeseed, sunflower, protein peas , fodder corn, grain corn, sugar beet, potato, sugar cane
2017	27, 958	90%	Soft wheat, hard wheat, barley, triticale, rapeseed, sunflower, protein peas, fodder corn, grain corn, sugar beet, potato, sugar cane, temporary meadow, permanent meadow, faba bean, soybean, fibre flax, oilseed flax, cereal mix, protein crops mix, forage mix

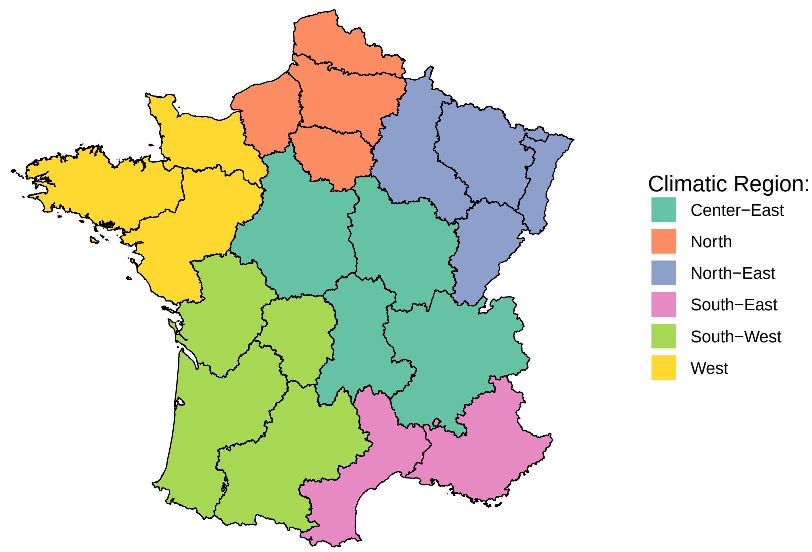
Source: AGRESTE.

C Appendix C: Construction of the Pseudo-Panel Database

C.1 Grouping by climatic region

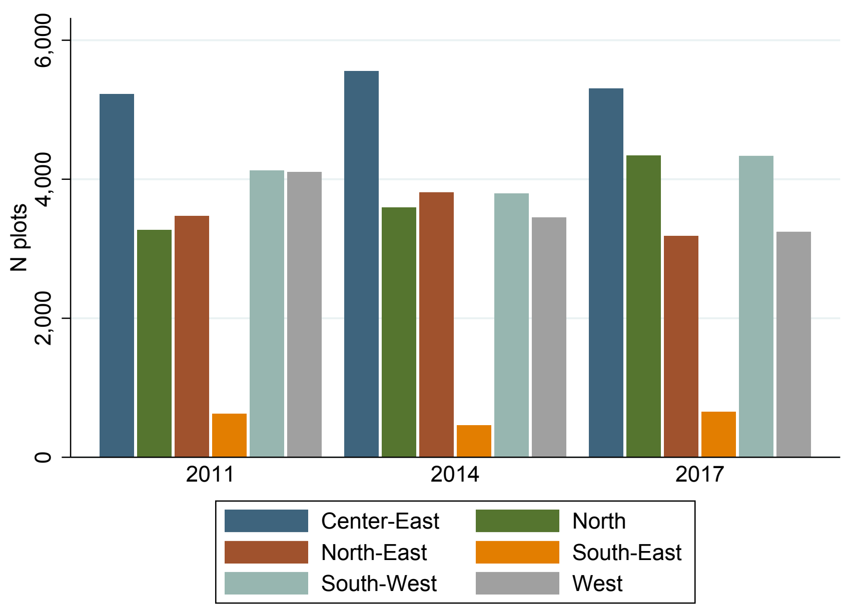
We group French administrative regions, as defined in the 2011 baseline data, within six climatic regions based on common climatic and soil conditions. The resulting groups are illustrated in Figure C.2 and the distribution of observations in Figure C.3. Figure C.4 illustrates the distribution of T1 and T2 farms in the cohorts, by region.

Figure C.2: Climatic region groups



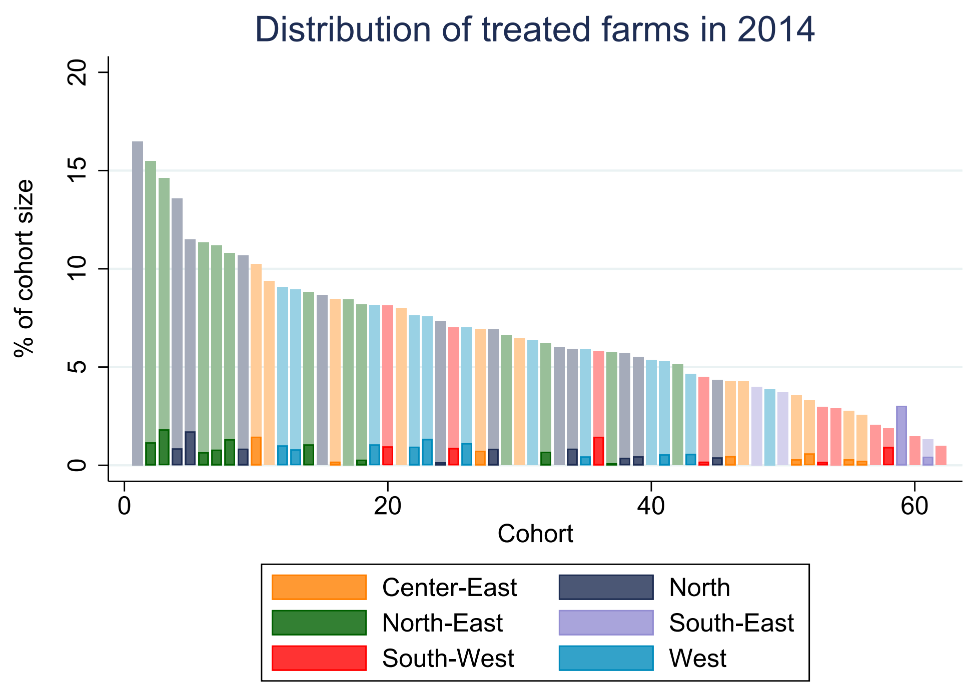
Note: Color should be used in print.

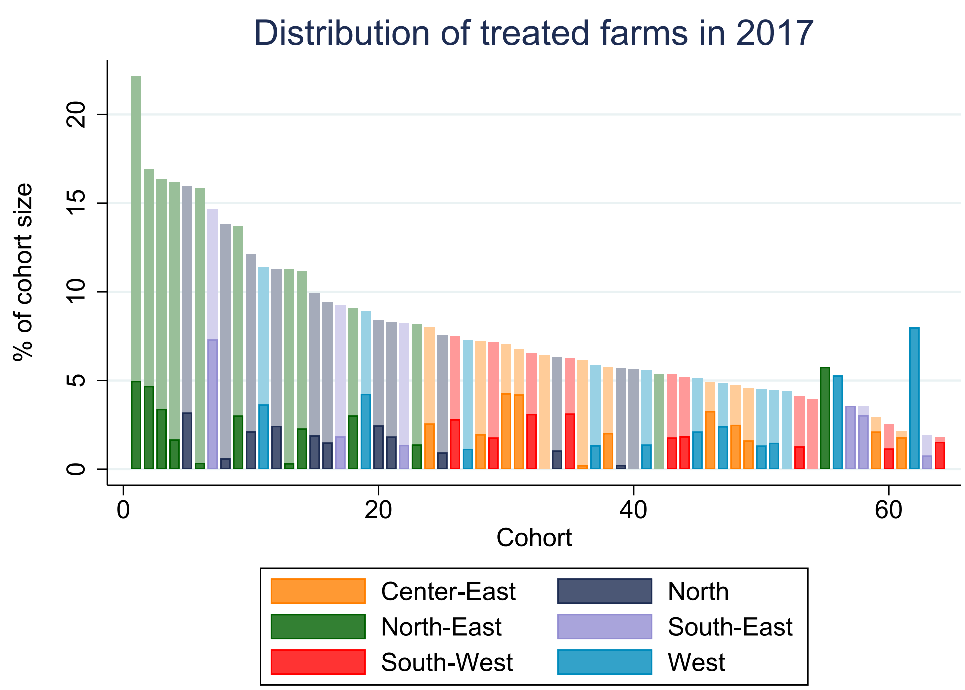
Figure C.3: Distribution of observations among regions



Note: Color should be used in print.

Figure C.4: Percentage of treated T1 and T2 farms in each cohort, broken down by region





Note: The share of T1 farms is indicated by the opaque bars and the share of T2 farms by the more transparent shades. Color should be used in print.

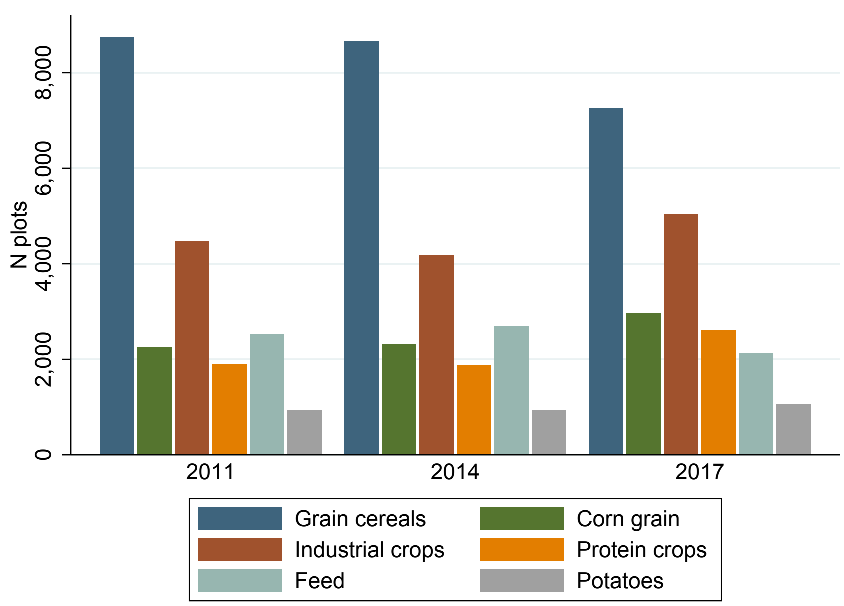
C.2 Grouping by crop type

We group observations by crop type based on similarities among crops. The groups are defined as follows:

1. Grain cereals: tender wheat, durum wheat, barley, triticale
2. Corn grain: grain corn
3. Industrial crops: rapeseed, sunflower, sugar beet, soybean, fiber flax, oilseed flax
4. Protein crops: proteaginous peas, fada bean
5. Feed: feed corn
6. Potatoes: potato

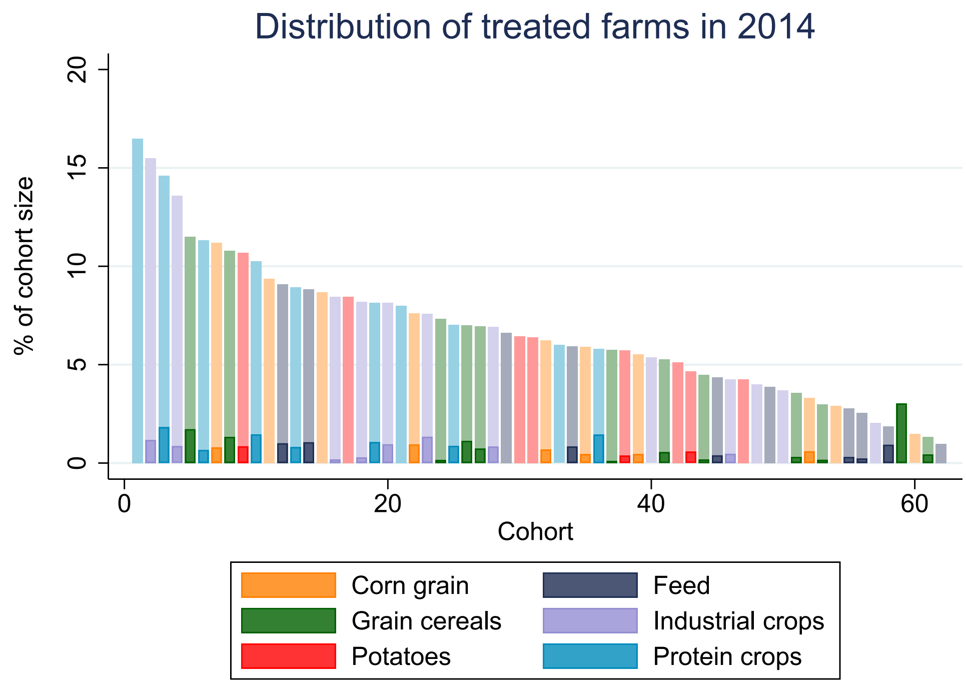
We exclude crop mix and meadow from the sample, as they are not surveyed in every year of our data. The distribution of observations among crop types is illustrated in Figure C.5, and the distribution of T1 and T2 farms among cohorts by crop type is illustrated in Figure C.6.

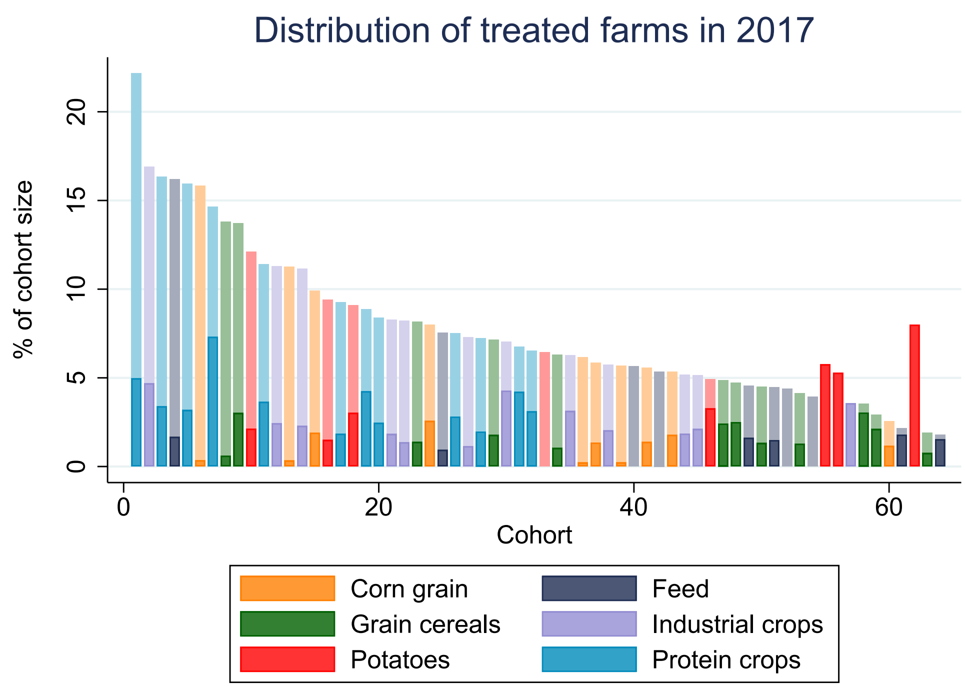
Figure C.5: Distribution of observations among crop types



Note: Color should be used in print.

Figure C.6: Percentage of treated T1 and T2 farms in each cohort, broken down by crop type



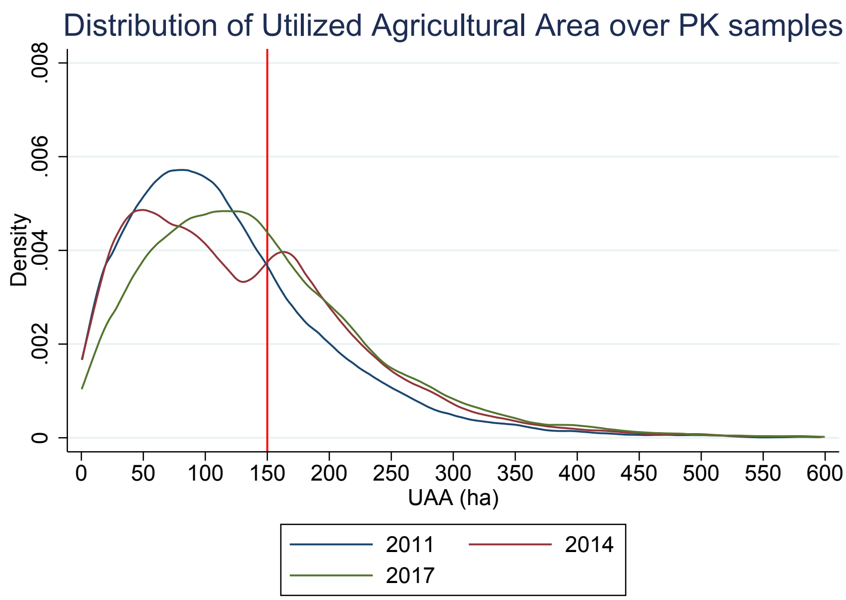


Note: The share of T1 farms is indicated by the opaque bars and the share of T2 farms by the more transparent shades. Color should be used in print.

C.3 Grouping by farm size

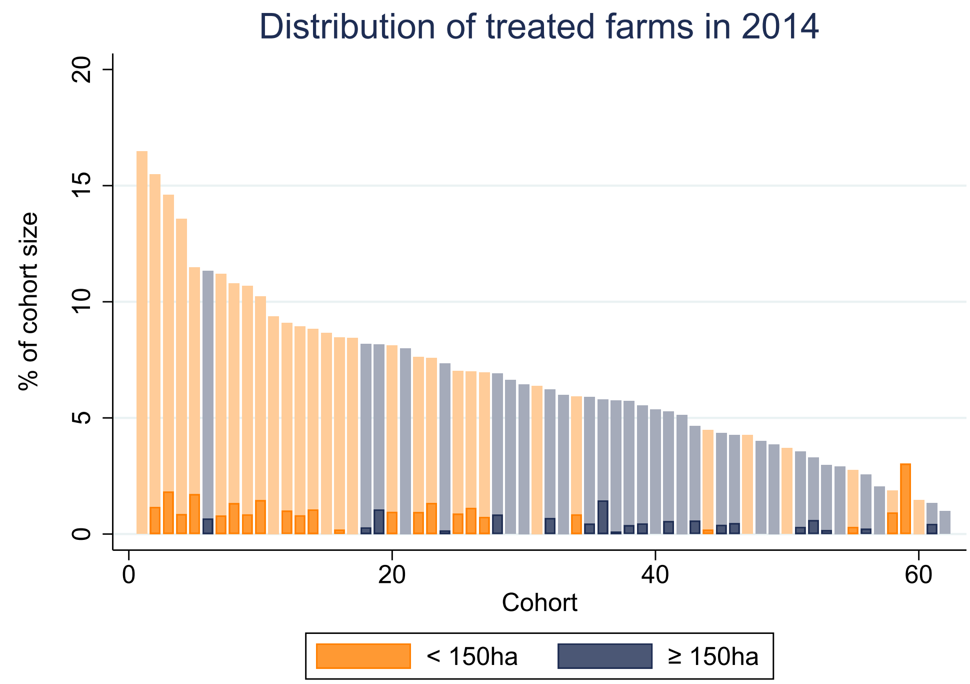
We separate small and large farms into two groups based on a cutoff at 150ha, which corresponds roughly to the median farm size in 2017 in our data. The distribution of UAA in the three survey rounds is illustrated in Figure C.7, and the distribution of T1 and T2 farms among cohorts, depending on farm size, is illustrated in Figure C.8.

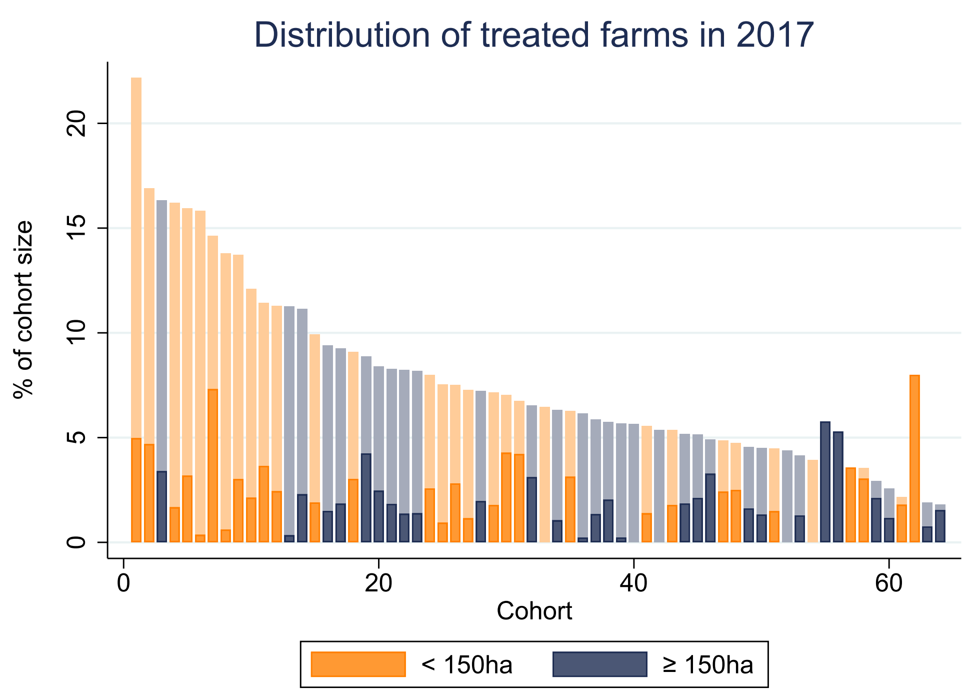
Figure C.7: Distribution of observations, depending on total UAA



Note: Color should be used in print.

Figure C.8: Percentage of treated T1 and T2 farms in each cohort, broken down by farm size (cutoff at 150ha)





Note: The share of T1 farms is indicated by the opaque bars and the share of T2 farms by the more transparent shades. Color should be used in print.

D Appendix D: Cross-effects of T1 and T2

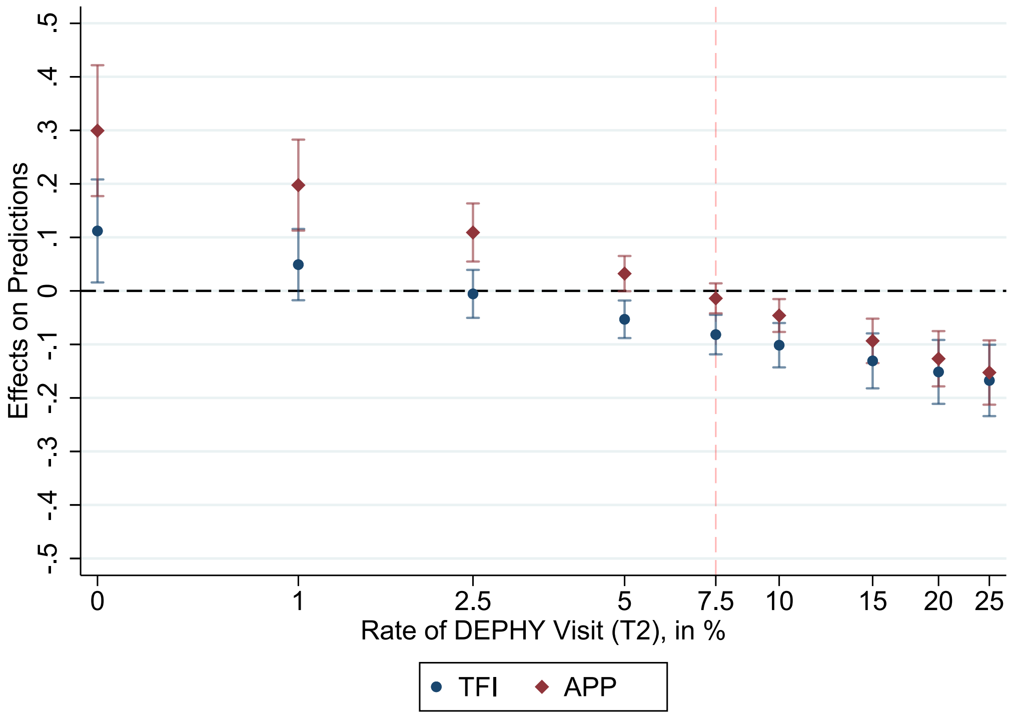
We estimate Equation 5 and display estimation results in Table D.2. The marginal effect of T1 on TFI is significantly positive when T2 is set to 0%, but becomes indistinguishable from zero for T2 between 2% and 3%, and significantly negative as T2 reaches 4% (see Figure D.9). The marginal impact of T2 on TFI is not significant at low levels of T1, and becomes significantly negative after T1 reaches 1% (see Figure 3 in Section D.2).

Table D.2: Cross-effects on pesticide use (Equation 5)

	(1) TFI	(2) APP
T1 × T2	-0.0714***	-0.1031***
	(0.0191)	(0.0197)
T1	0.1120**	0.2771***
	(0.0491)	(0.0534)
T2	0.0202	0.0585**
	(0.0272)	(0.0231)
Constant	1.8549***	2.3638***
	(0.0249)	(0.0229)
Organic label	Yes	Yes
AES	Yes	Yes
Year FE	Yes	Yes
Cohort FE	Yes	Yes
N	190	190

Notes: TFI refers to the Treatment Frequency Index. APP refers to the number of application rounds. T1 is the share of participating farms in the cohort and T2 is the share of visiting farms in the cohort. All variables are in IHS. Reference year is 2011. Robust standard errors at the cohort level are in parenthesis. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Figure D.9: Marginal impact of T1 at various levels of T2 (Equation 5)



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