Social Learning for the Green Transition Evidence from a Pesticide Reduction Policy

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Evidence from a Pesticide Reduction Policy

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Abstract

Social learning and diffusion of innovations through peers can be a key component of the agroecological transition, as it contributes to the generalization of good practices and improves the efficiency of public policies by increasing the number of farmers reached without 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 farming practices and encourage knowledge diffusion beyond the scope of farms enrolled in the program. We applied a quasi-experimental approach to pseudo-panel data collected at national scale and found that doubling the proportion of participants would reduce pesticide use by about 10% within representative cohorts on average. Besides, we found an additional effect of similar magnitude on farms that report having participated to demonstration visits to the farms trained by the program. These results suggest that agricultural training programs are likely to generate spillover effects at lower cost.

JEL Codes: Q15; Q18; Q25; Q28; Q53.

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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 larger changes, as individuals close to the target group are directly influenced by its actions. When it comes to the green transition, the spread of green agricultural technologies is a central question. 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 it would entail. In this context, observational learning can thus 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 happen. Moreover, it is often difficult to identify and measure it 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 the challenge of agroecological transition is particularly important. 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 enacted a national plan in 2008, with the aim to reduce the use of pesticides by 50% overall by 2018.

[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.

As part of this plan, 3,000 volunteer farmers have been 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, these farms were then invited to open their doors for demonstration visits, with the aim of passing on the knowledge accumulated during the program to neighboring farms that might be interested in learning these new practices. Monitoring data from farms enrolled in the program indicate that they have indeed succeeded in significantly reducing their use of pesticides in the space of a few years. Two question remain, however, regarding the truly additional effect of the program. Firstly, is there a real margin for improvement in the practices of these farms that have self-selected in the program, compared to what they would have succeeded in doing outside the program? Then, with regard to the visiting farms that only benefited from second-hand training (and self-selected too), was this enough to trigger a real change in their practices afterwards?

We ran an empirical analysis built on repeated cross-sectional data about phytosanitary practices collected from a representative sample of around 28,000 plots used for the cultivation of field crops, which represent nearly 95% of the country's utilized agricultural area. Following the approach first popularized by Deaton (1985), we constructed a pseudo-panel of 64 cohorts using three essential criteria when it comes to the choice of agricultural practices: crop type, location and farm size. We then ran a fixed effects model regression to estimate the effects of the program on pesticide use in the cohorts. Our results point to a 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 10% on average across cohorts. Besides, we evaluated spillovers of the program on farms that reported having participated to visits at an enrolled farm and found again a significant decrease in pesticide use of similar magnitude (while the proportion of visiting farms is higher than the one of enrolled farms). This finding confirms the presence of knowledge spillovers in the neighbourhood 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 first beneficiaries of the program. This result thus highlights the importance of social learning and the diffusion of knowledge to support transitions in the context of developed countries, as has been demonstrated in other contexts.

We provide an overview of relevant studies in the literature that studied peer effects and 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 social networks of farmers has become an increasingly important topic in the literature in recent years. First introduced by Romer (1986) and Lucas (1988) as a factor of endogenous growth, social learning has then been thoroughly studied in various microeconomics contexts. By social learning, we here refer to the diffusion of knowledge and practices throughout social interactions between economic agents. Social interactions are likely to affect individual behaviour through observational learning, information transmission, change of expectations, or a change of 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 lead 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 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 so-called endogenous effect). When information about 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 proposed 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 farmers networks. Notably, Conley and Udry (2010) collected data about who farmers know and talk to frequently 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", with stronger responses in cases were the neighbor is an experienced farmer or a farmer with similar wealth 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 role of "communicator" about a new agricultural technology to "peer farmers" is more efficient for promoting the technology to other farmers than when the knowledge is provided by a government-employed extension worker or a so-called "lead farmers" who are nevertheless more educated than the average farmer of the village. This result goes to show that farmers are most convinced by the advice of others who face agricultural conditions that are 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 it thus is most efficient to design policies that address incentives to 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 distributed blue spoons designed to help farmers measure the right amount of fertilizers to use on their plots to randomly selected farmers, and found that knowledge and ownership of the blue spoon did spread through social networks of friends of the farmers that received it 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 spoon 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 report an increase in the knowledge of the blue spoon among farmers in the same cluster than treated farmers, but not an increased take-up of the technology. This suggest that the "subjective value" of knowledge differs based on the perceived reliability of the farmer spreading the information. These findings highlight again the importance of targeting the right individuals when trying to incentivize technology adoption through social learning among farmers networks.

The present paper aims at studying 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. Further, the literature focuses on the diffusion of technologies that aim to improve productivity for adopting farmers. When looking at environmental policies, the benefits of adoption are less obvious or at least not immediate for farmers. We thus can expect lower adoption rates in such contexts, although the learning mechanisms may well be similar to those described in the literature so far. 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 in the literature (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 first 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. being a participating farm) and indirect (i.e. attending a demonstration visit hosted by a DEPHY farm) effects 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 design allows us to control for confounding factors that may drive outcomes of both participating and visiting

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

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 applied the fixed-effect estimator to a panel data model to estimate the direct effect of the DEPHY program as well as spillover effects on pesticide use across cohorts.

3.1 Data

The dedicated statistical and prospective service of the French Ministry in charge of Agriculture produces extensive surveys of agricultural practices on a regular basis, which are available upon authorization from the Ministry. The agricultural practices surveys cover representative samples of plots for various types of crops, including field crops.[4] The most recent iterations of the agricultural practices survey for field crops were in 2011 and 2017,[5] with an additional so-called intermediary survey conducted in 2014, specifically on phytosanitary practices. Our database therefore includes one observation prior to the start of the program (2011) and two observations of practices during the program (2014 and 2017). The surveys also include questions about labels and environmental schemes.

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). The TFI was developed in the 1980s in Denmark and is now widely used worldwide, including by French policymakers as the main monitoring indicator of the Ecophyto plan (Pingault et al., 2009). It captures the number of reference doses applied per hectare, taking into account the recommended dosage for each product, as

[4]A detailed description of data sources is provided in the Appendix B. The sampling procedure follows a two-step procedures. First, field crop farms are stratified depending on whether they practice organic farming, their location (at the department level for non-organic farms and regional level for organic farms) and the total cultivated area of the farm. Then, 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 conclusion at the national scale.

[5]The scope of the surveys evolved over time to include more species and also cover more plots.

well as the Share of Treated Area (STA), i.e. the surface to which the product is applied. In the survey, the TFI is computed as follows:

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

with 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 utilised agricultural area. Based on this formula, the TFI is set to be equal to 1 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 about pesticide pressure, provided that the farmer used the recommended dose, information which however remains unobserved.

While the TFI was computed for each chemical product (herbicides, fungicides, insecticides), for the purpose of the present analysis we focused on the aggregated TFI, which captures the overall change of practices, since the specific products through which this change occurs, if any, is beyond the scope of our analysis and is more of an agronomic question. More specifically, we focused on chemical TFI, excluding "organic pesticides" (i.e. pest management products that rely on natural active products such as copper) since the program promotes the reduction of chemical pesticides, not of organic systems.

We then further decomposed the terms of equation 1:

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

with D_i the dose of active product in product i and APP_i the number of pesticide application rounds. By doing so, we looked at the number of application rounds APP_i as an additional outcome to explore a potential channel that could drive TFI reduction. As the reference dose is fixed for a given period, a change of TFI_i without any change of APP_i nor STA_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. We used this information to build control variables that equal to 1 if the plot is cultivated according to the organic label requirements, and 0 otherwise.

3.3 Treatment Variables

Around 1,200 French farms entered the program before 2013. The 2014 and 2017 surveys provide us with two important pieces of information about the surveyed plot, namely, whether the farmer is a participant in the DEPHY program or whether he has already participated in a demonstration visit offered by the DEPHY program. We thus built two binary treatment variables that measure direct or indirect participation in the program. The first level of treatment (hereafter T1) is the membership to the DEPHY network, materialized by the agreement with the DEPHY terms of reference (the so-called *cahier des charges*). The 2017 agricultural practices questionnaire includes a question about commitment of the respondent's farm to DEPHY, which we used to identify direct participants in the program. For the year 2014, DEPHY participants were identified through data directly collected by the Ecophyto plan.[6] In our data, the treatment variable T1 then equals one if the farmer was a member of the program in 2014 or 2017 and zero elsewhere.

We then investigated knowledge and information spillovers through the construction of another treatment variable, T2, taking on 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 of the program and attend the visits organized by the program.

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 then 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.2 in Appendix C.

2. Crop type: six types of crops, see Figure C.3 in Appendix C.

3. Utilized Agricultural Area (UAA): two groups were defined using a cutoff at 150ha, see Figure C.4 in Appendix C.

[6] Agrosyst data accessed in May 2017.

In theory, this procedure would have generated 72 cohorts per year. In practice however, as some categories were empty, we ended up with 52 cohorts in 2006, 64 cohorts in 2011 and 2017 and 62 in 2014. The average cohort size is around 330 farms each year (Table 1).

Table 1: Cohort characteristics

	Number of farms	Number of cohorts	Cohort size Mean	SE	Min	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

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

We then took these cohorts as units of observation, aggregating the variables of interest within each of them. When it comes to the treatment variables, we thus computed the share of treated individuals within each cohort. The two treatment variables are therefore defined as the share of participating farms (T1) and the share of visiting farms (T2) within each cohort. Both treatment variables are set to 0 in 2011, as enrollment in the program effectively began in 2012.

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; α, β_1, β_2, γ are the parameters to be estimated, and ϵ_{ct} is the error term.

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 allows us in particular to check whether the level of T1 influences the impact of T2; that is, if having a larger proportion 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:

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

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

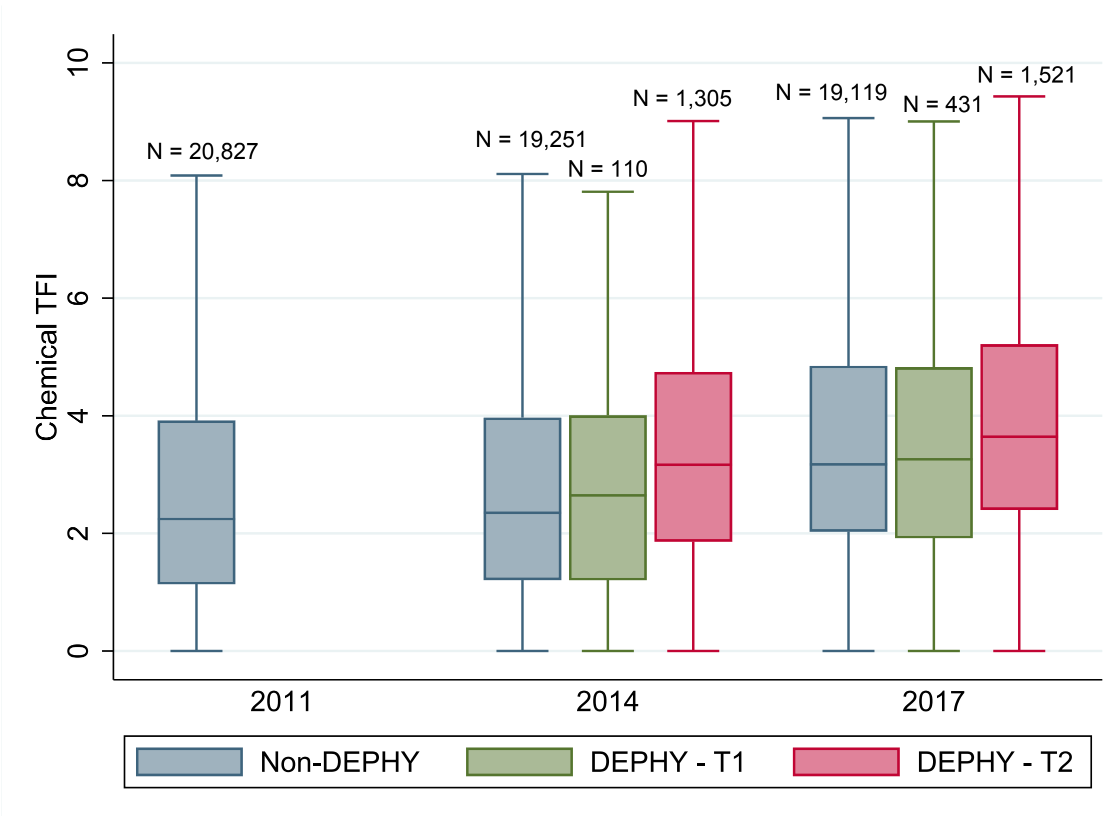
The main characteristics of the 20,000 plots used to construct the cohorts are presented in Table 2. The average overall Utilized Agricultural Area (UAA) increased over the period to reach 145 hectares in 2017, and so did the average plot surface, which reaches 7 hectares. The number of application rounds (APP) remained stable, around 5 per year, and the treatment frequency index for all chemical pesticides (TFI) increased on average over the period, going from 3 to 4 on average. The share of organic plots increased between 2011 and 2014 and remained stable between 2014 and 2017. Lastly, the proportion of farms that joined the DEPHY program increase over time (1% in 2014 and 2% in 2017) and as well as the proportion of visiting farms (6% in 2014 and 7% in 2017).

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
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	

The distribution of chemical TFI among DEPHY farms (whether participating or visiting ones) in 2014 and 2017 is displayed in Figure 1. Quite surprisingly, DEPHY farms are not characterised 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 is however consistent with the stated strategy of the program not to recruit farms that were already performing better than the rest of French farms in terms of pesticide use.

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



Note: T1 refers to participating farms and T2 to visiting farms.

Cohort Data

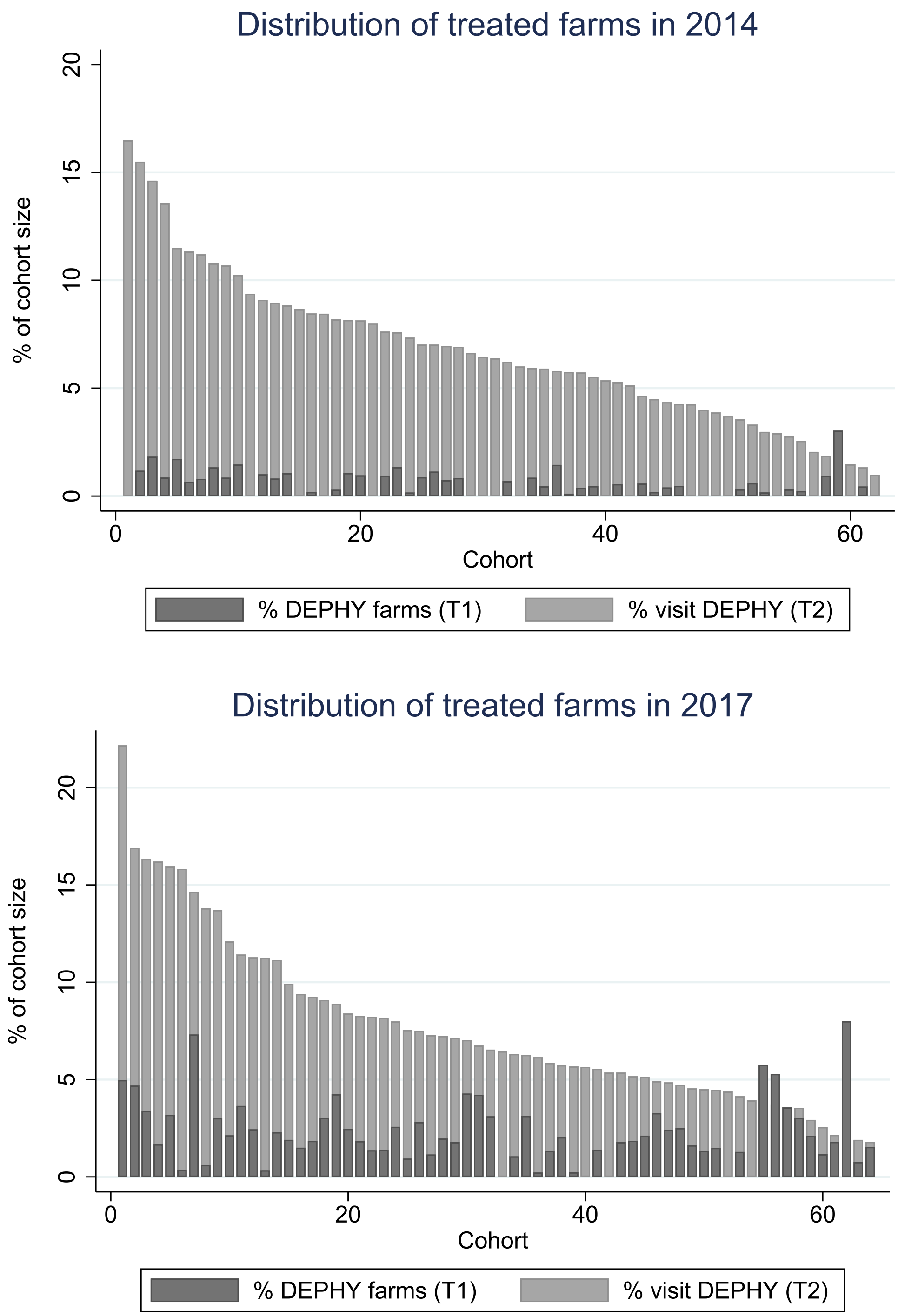
The distribution of treated farms within the cohorts is displayed in Figure 2, with summary statistics presented in Table 3. The proportion of participating farms ($T1 = 1$) ranges from 0% to 3.03% in 2014, and from 0% to 8% in 2017. The proportion of visiting farms ($T2 = 1$) is always greater than 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 moreover shows that the share of participating farms and of visiting farms in each cohort does not seem to be strongly correlated, which suggest that the proportion 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.5, C.6 and C.7.)

Table 3: Proportion of treated farms in the sample

	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: Proportion of treated farms in each cohort



Note: Cohorts are ranked based on the proportion of visiting farms ($T2 = 1$) for readability purposes. 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 0 in our data. This transformation also reduces the likely 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 one-percent 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 size and brought to light the necessity to use robust standard errors in regression models, which we applied throughout the analysis.

Results of the estimation of Equations 3 and 4 are presented in Table 4.

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

	(1) TFI	(2) TFI	(3) APP	(4) APP
T1	-0.0772***		0.0130	
	(0.0208)		(0.0218)	
T2	-0.0551**		-0.0496	
	(0.0266)		(0.0318)	
T1 × 2014		-0.0299		0.0217
		(0.0324)		(0.0401)
T1 × 2017		-0.0966***		0.0089
		(0.0233)		(0.0253)
T2 × 2014		-0.0148		0.0022
		(0.0246)		(0.0291)
T2 × 2017		-0.1132***		-0.1119***
		(0.0327)		(0.0390)
Constant	1.8926***	1.8904***	2.3880***	2.3883***
	(0.0230)	(0.0218)	(0.0251)	(0.0224)
Organic label	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
N	190	190	190	190

Notes: T1 is the proportion of participating farms in the cohort and T2 is the proportion of visiting farms in the cohort. All variables are in IHS. Reference year is 2011. Robust Standard Errors at the cohort level in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Impact on participating farms (direct effect)

Table 4 shows that the marginal effect T1 on chemical TFI is negative and significant at the 1% level overall (column 1). When looking at the year by year effect, it is only significant in 2017. This shows a significant impact of the DEPHY network on pesticide use which was not yet present in 2014, as the implementation of the program had just begun. The magnitude of the coefficient in 2017 is roughly of 0.1, meaning that increasing the share of T1 farms in a cohort by 1% is associated on average with a decrease of TFI of 0.1%. Doubling the share of T1 farms in the cohorts (i.e., increasing it by 100%) would thus imply a 10% reduction of TFI.

The effects on the number of application rounds are not significant regardless of the year. This suggest that the underlying mechanism behind the decrease in TFI is not driven by a change in the number of pesticide application (APP). Therefore, this result suggests that the impact of the DEPHY network on pesticide use is mostly driven by a change in the doses of pesticides applied by T1 farmers.

Impact on visiting farms (spillover effect)

Table 4 reports a significant negative effect of T2 on TFI, which occurs between 2014 and 2017. Similar to the impact of T1, the year by year interaction shows that the impact of visits and demonstration days became clearly established after the program had been implemented for some years. 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 decrease of TFI by 10%.

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 0. While this could suggest that T2 farms reduce pesticide use through different channels than T1 farms, it is more likely that the effect on treatment frequency is estimated more precisely for T2 farms than for T1. Indeed, T2 farms represent a larger share of the cohorts than T1 farms, and their effect is estimated more precisely. This would imply that the lack of effect on number of application rounds we observe for T1 farms is due to a lack of precision in our data, rather to a lack of impact in reality.

Our results show that increasing the number of T2 farms is a relevant channel to further induce pesticide reduction among farmers. However, increasing the number of farmers that attend visits and demonstration days held by participating farms creates a burden for the hosting farms. We explore the relationship between T1 and T2 by estimating Equation 5. Results are displayed in Table 5.

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

	(1) TFI	(2) APP
T1	0.1441**	0.2993***
	(0.0555)	(0.0624)
T2	0.0380	0.0708***
	(0.0262)	(0.0225)
T1 × T2	-0.0893***	-0.1155***
	(0.0204)	(0.0225)
Constant	1.8958***	2.3922***
	(0.0210)	(0.0197)
Organic label	Yes	Yes
Year FE	Yes	Yes
Cohort FE	Yes	Yes
N	190	190

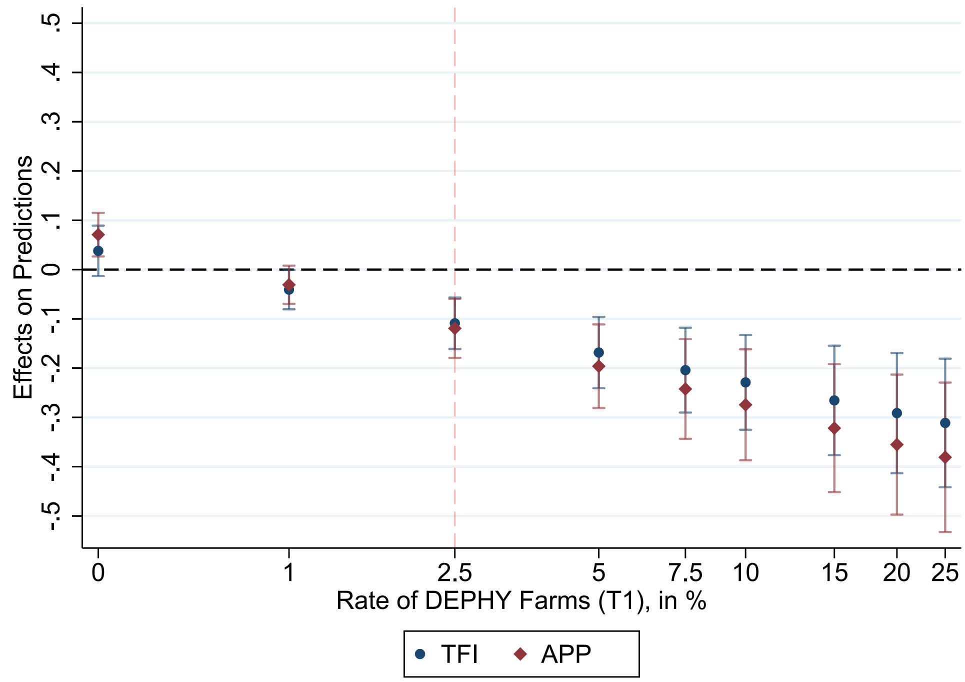
Notes: The dependent variables and all quantitative explanatory variables are in IHS.

Robust Standard Errors at the cohort level in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We also use the estimates from Table 5 to compute the marginal effect of T2 conditional on several levels of T1. Results are displayed in Figure 3. We find that, when estimated at the average share of T1 in the cohorts in 2017, the effect of T2 on both TFI and number of application rounds is negative and significant. This is consistent with previous results reported in Table 4. Further, Figure 3 depicts the evolution of the impact of T2 when T1 increases: the higher the share of T1 farms, the more pronounced the impact of T2 farms. Increasing the share of T1 in the population allows for more visits and demonstration days, which increases the impact of T2. However, this relationship is not linear (recall that we apply an IHS transformation to our dependent and explanatory variables). The marginal effect of T2 when T1 is equal to 10% of the population is roughly 0.24, meaning that for this level of T1, doubling the share of T2 farms would lead to a TFI reduction of 24%. For T1 equal 20% of the population, this suggests that doubling the share of T2 farms would lead to a TFI reduction of roughly 30%.

Figure 3: Marginal effect of T2 conditional on T1



Note: The red doted line illustrates the average share of T1 in the cohorts in 2017. Estimated effects are computed from Table 5 for the two outcome : TFI (Treatment Frequency Index) and APP (number of application rounds). 95% CI.

5 Discussion and Robustness Checks

5.1 Other Pesticide Reduction Schemes

One concern with our identification strategy is the existence of time-varying factors that would influence both DEPHY take-up rate within a cohort and pesticide use. For instance, if there existed a specific regional communication strategy for the reduction of pesticides that targets farms of a given size that produce a certain type of crops, this would encourage all farms of the cohort defined by the intersection of these characteristics to reduce pesticide use, and also encourage farms to apply to join the DEPHY network. However, it seems unlikely that such campaigns would be conducted randomly. We can plausibly assume that the occurrence of a campaign would be correlated with underlying cohort characteristics that would be absorbed by the cohort fixed effects in the regression model. Moreover, it is more likely that information campaigns would be conducted at a larger scale and be (at least partly) absorbed by year fixed effects. And lastly, the number of farms that are able to join the network is limited, making it unlikely that it can drastically increase due to a competing pesticide reduction campaign.

However, we introduced an additional control variable in the regression in order to further control for potential confounding factors: the share of farms in the cohorts that are enrolled in pesticide-related Agro-Environmental Schemes (AES) in 2011 and 2014, which became Agro-Environmental and Climate Schemes in 2015. These European measures provide subsidies for farms that are committed to environmental practices, and the share of pesticide AES farms in each cohort could be correlated with pest management practices and with the share of DEPHY farms. Indeed, the two programs are not mutually exclusive and can attract similar farmers. As explained in Section 4.1, the variable that captures enrollment in these schemes differs in 2017 and in the two previous survey years due to the evolution of the legislation. We present results using the variable that captures specifically enrollment in pesticide related schemes in Table 6 below, and results with enrollment in a generic scheme in 2017 in Table D.2 in Appendix D. Our results are robust to the addition of this new control variable.

Table 6: Direct and spillover effects on pesticide use (Equations 3 and 4 including additional controls)

	(1) TFI	(2) TFI	(3) APP	(4) APP
T1	-0.0734***		0.0171	
	(0.0203)		(0.0205)	
T2	-0.0552**		-0.0497	
	(0.0252)		(0.0300)	
T1 × 2014		-0.0436		0.0005
		(0.0332)		(0.0387)
T1 × 2017		-0.0879***		0.0225
		(0.0250)		(0.0277)
T2 × 2014		-0.0142		0.0031
		(0.0248)		(0.0293)
T2 × 2017		-0.1102***		-0.1073***
		(0.0317)		(0.0355)
Constant	1.8662***	1.8751***	2.3586***	2.3643***
	(0.0274)	(0.0269)	(0.0306)	(0.0291)
Organic label	Yes	Yes	Yes	Yes
Pesticide AES	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
N	190	190	190	190

Notes: The dependent variables and all quantitative explanatory variables are in IHS. Reference year is 2011.

Robust Standard Errors clustered at the cohort level in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Small Cohorts

Another potential concern 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 excluded 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 some cohorts are small in multiple years of our pseudo-panel. In total, they amount to ten observations over the years. They are presented in Table 7. We reran the same estimations after excluding them from the sample. Results are reported in Table 8 below. Overall, they do not contradict previous findings, which suggest that the presence of very small cohorts in the sample does not affect the validity of ours analysis.

Table 7: 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 8: Direct and spillover effects on pesticide use without small cohorts (Equations 3 and 4)

	(1) TFI	(2) TFI	(3) APP	(4) APP
T1	-0.0919***		-0.0084	
	(0.0234)		(0.0208)	
T2	-0.0356		-0.0172	
	(0.0261)		(0.0260)	
T1 × 2014		-0.0169		0.0202
		(0.0315)		(0.0399)
T1 × 2017		-0.1189***		-0.0149
		(0.0221)		(0.0193)
T2 × 2014		-0.0126		0.0129
		(0.0241)		(0.0292)
T2 × 2017		-0.0882***		-0.0692**
		(0.0314)		(0.0289)
Constant	1.8785***	1.8723***	2.4002***	2.3961***
	(0.0245)	(0.0237)	(0.0230)	(0.0221)
Organic label	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
N	180	180	180	180

Notes: The dependent variables and all quantitative explanatory variables are in IHS. Reference year is 2011.

Robust Standard Errors clustered at the cohort level in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Specification Check

Our main analysis relies on the estimation of Equation 5, in which both T1 and T2 farms are included. The rationale behind this specification is that T1 and T2 are correlated since they both depend on the intensity of the implementation of the DEPHY program in a given region and for a given type of farms, as we rely on farm characteristics to build our pseudo-panel.

Therefore, we cannot estimate the impact of T1 and T2 separately as we would then likely introduce an omitted variable bias.

However, including both variables in our model introduces a risk of having a bad control (Angrist and Pischke, 2009): indeed, demonstrations and visits can be interpreted as a channel through which DEPHY members ($T1 = 1$) achieve pesticide reduction in their cohort. This concern is partly alleviated by the fact that, by construction, our T2 variable is not limited to farmers that attended a demonstration or visit organized by a participating farm from their cohort, since our data does not allow us to identify which demonstration or visit T2 farmers have attended. The link between T1 and T2 in each cohort is therefore not systematic, even if it is likely that farmers would rather chose to visit nearby farms that closely resemble their own.

In order to test whether our results are confounded by the simultaneous inclusion of T1 and T2 in our model, we build two alternative pseudo-panels in which we exclude participating farms ($T1 = 1$) and visiting farms ($T2 = 1$) respectively before aggregating the data. This allows us to test the impact of T1 on pesticide use in a hypothetical context where there is no demonstration or visits, and similarly, to test the impact of T2 in a context without T1. While none of these two cases reflect the reality of the DEPHY program, they allow us to compute the "pure" effect of each level of treatment independently.

We estimate Equation 6 on an alternative pseudo-panel dataset from which we excluded visiting farms ($T2 = 1$), and Equation 8 on an alternative pseudo-panel dataset from which we excluded participating farms ($T1 = 1$).

$$Y_{ct} = \alpha + \beta T1_{ct} + \mu_c + \nu_t + \gamma X_{ct} + \epsilon_{ct}, \tag{6}$$

$$Y_{ct} = \alpha + \beta_1 T1_{ct} + \beta_2 T1_{ct} \times Year_t + \mu_c + \nu_t + \gamma X_{ct} + \epsilon_{ct}, \tag{7}$$

$$Y_{ct} = \alpha + \beta T2_{ct} + \mu_c + \nu_t + \gamma X_{ct} + \epsilon_{ct}, \tag{8}$$

$$Y_{ct} = \alpha + \beta_1 T2_{ct} + \beta_2 T2_{ct} \times Year_t + \mu_c + \nu_t + \gamma X_{ct} + \epsilon_{ct}. \tag{9}$$

Results are presented in Tables 9 and 10. The β coefficient associated with T1 alone is negative and statistically significant at the 1% level when considering the impact on chemical TFI, but not for the number of application rounds. As in our main findings, the effect occurs between 2014 and 2017. As for T2, its impact on TFI is negative and significant at the 1% level, and its impact on the number of application rounds is also negative and significant at the 10% level. Both effects occur between 2014 and 2017. The magnitude of the effect is in line with our previous findings when looking at the average share of T1 and T2 in the cohorts. These results confirm the presence of a direct (T1) and spillover (T2) impact of the DEPHY network on TFI.

Table 9: Direct effect on pesticide use, excluding visiting farms from the individual data

	(1)	(2)	(3)	(4)
	TFI	TFI	APP	APP
T1	-0.0776***		0.0056	
	(0.0217)		(0.0225)	
T1 $\times$ 2014		-0.0108		0.0417
		(0.0319)		(0.0314)
T1 $\times$ 2017		-0.1057***		-0.0096
		(0.0248)		(0.0268)
Constant	1.8694***	1.8674***	2.3645***	2.3634***
	(0.0246)	(0.0248)	(0.0245)	(0.0243)
Organic label	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
N	190	190	190	190

Notes: The dependent variables and all quantitative explanatory variables are in IHS. Reference year is 2011.

Robust Standard Errors clustered at the cohort level in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Spillover effects on pesticide use, excluding participating farms from the individual data

	(1) TFI	(2) TFI	(3) APP	(4) APP
T2	-0.0638***		-0.0512*	
	(0.0233)		(0.0300)	
T2 × 2014		-0.0114		0.0008
		(0.0240)		(0.0272)
T2 × 2017		-0.1242***		-0.1113***
		(0.0300)		(0.0354)
Constant	1.8681***	1.8700***	2.3585***	2.3604***
	(0.0242)	(0.0235)	(0.0262)	(0.0241)
Organic label	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
N	190	190	190	190

Notes: The dependent variables and all quantitative explanatory variables are in IHS. Reference year is 2011.

Robust Standard Errors clustered at the cohort level in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.4 Replication on Vineyards

Our cross-sectional data does not allow us to analyze DEPHY spillovers at the individual level, as we aggregate the data to form a pseudo-panel in order to be able to introduce fixed effects. The surveys we exploited to build this pseudo-panel are also ran on different types of crops, and the vineyard survey is implemented on a panel of 4,057 crops. Lapierre, Sauquet, and Subervie (2019) exploit this survey and merge it with detailed data collected by the DEPHY network to compute the impact of the program on TFI. We extend their analysis by exploring the spillovers of the program through visits and demonstration days (T2). We do not present results for participating farms (T1), as this information is not available in our data. We estimate Equations 10 and 11, where i denotes individual crops. We extend the analysis to a third measure of pesticide use, the share of treated area (STA), which is specifically relevant here as reducing intra-row treatments is a strong lever of pesticide reduction in vineyards.

$$Y_{it} = \alpha + \beta T2_{it} + \mu_i + \nu_t + \gamma X_{it} + \epsilon_{it}, \tag{10}$$

$$Y_{it} = \alpha + \beta_1 T2_{it} + \beta_2 T2_{it} \times Year_t + \mu_i + \nu_t + \gamma X_{it} + \epsilon_{it}. \tag{11}$$

Results are presented in Table 11. Column (1) reports a negative and significant effect of T2 on chemical TFI in vineyards, which confirms the existence of knowledge and information spillovers through the visit and demonstration days organized by DEPHY farms. Column (2) shows that this effect became apparent as soon as 2013. This contrasts with our findings on field crop farming, where the effect only occurred after 2014. Here, the effect can be interpreted directly at the individual level: attending a visit or demonstration day organised by a participating farm reduces chemical TFI by approximately 0.4 points for vineyards. When looking at sub-components of TFI, we find a negative and significant effect of T2 on the share of treated area. On the other hand, the overall effect on the number of application rounds is insignificant. Overall, these results are consistent with our main findings on field crops farming.

Table 11: Spillover effects on pesticide use on T2, vineyards

	(1) TFI	(2) TFI	(3) APP	(4) APP	(5) STA	(6) STA
T2	-0.4164***		-0.0934		-0.4073**	
	(0.1399)		(0.2078)		(0.1932)	
T2 × 2013		-0.4274**		-0.4905**		-0.4454*
		(0.1835)		(0.2311)		(0.2470)
T2 × 2016		-0.4061**		0.2791		-0.3715
		(0.1967)		(0.3072)		(0.2637)
Constant	12.3443***	12.3443***	16.3332***	16.3330***	94.5476***	94.5476***
	(0.0435)	(0.0435)	(0.0649)	(0.0649)	(0.0571)	(0.0571)
Organic label	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,171	12,171	12,171	12,171	12,171	12,171

Notes: Robust Standard Errors at the individual level in parenthesis. Reference year is 2010.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 proportion of farms enrolled in the DEPHY network would reduce chemical TFI by 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 participated to a visit or a demonstration held at a participating farm also changed their pest management practices due to the program. Indeed, our analysis shows that the marginal effect of increasing the share of farms participating in such DEPHY events on chemical TFI 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 in the program, 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 at 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 impact of a peer network with technological assistance program on agricultural practices. Future research could focus on building a measure of spatial spillovers and explore further their impact on pesticide use, following the approach developed by Missirian (2020). Another possible follow-up on 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 be a way to identify farmers that regularly interact with DEPHY members and then questions whether or not these interactions led to change of 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 "Ecophyto 30,000 groups" is to generalize the findings from 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.

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A Appendix A

A.1 The DEPHY Network

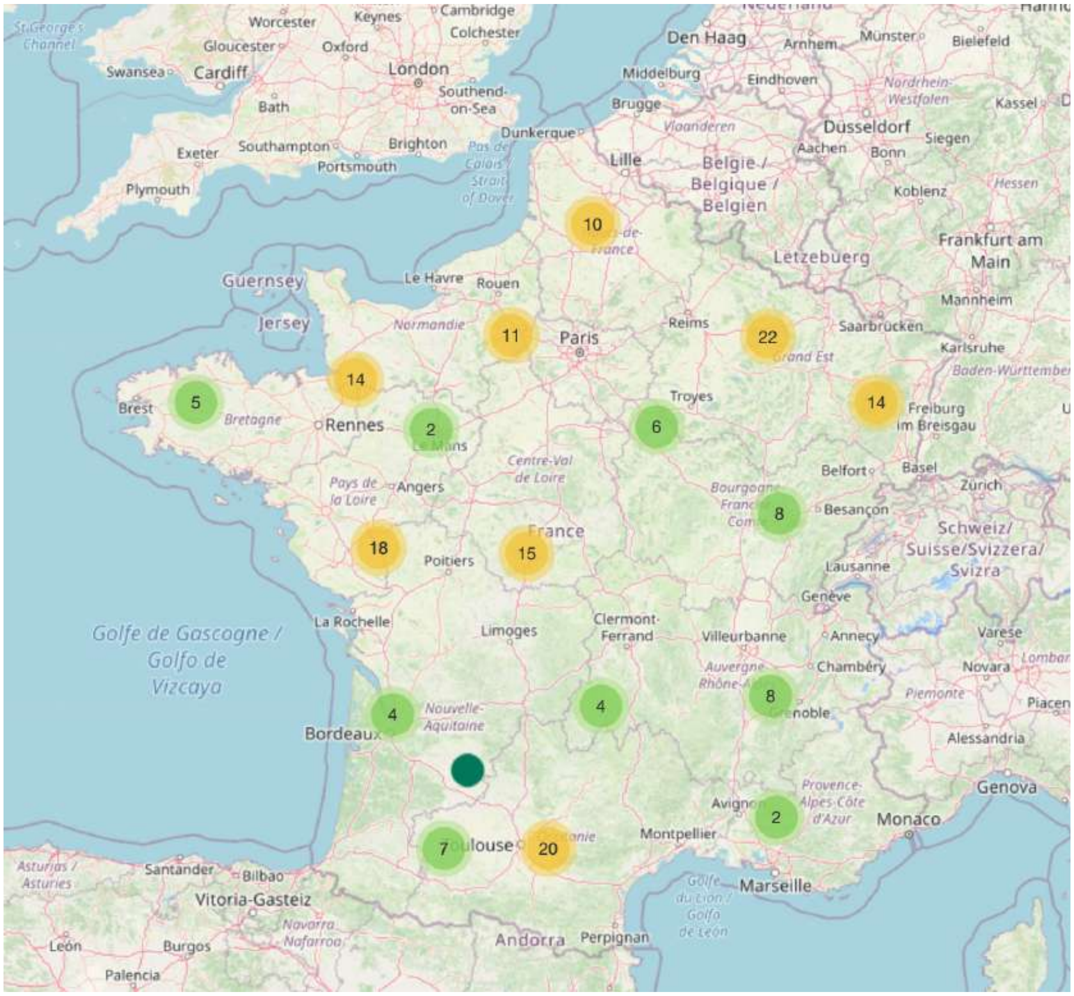
Since 2012, the French Ecophyto plan finances the DEPHY (Demonstrate, Experiment and Produce references on low pHYtosanitary systems) program, a national peer-network of 3000 farms committed to reducing pesticide use with the technical help of trained advisors. Member farms voluntarily joined the program between 2011 and 2016. They share the same goal to reduce pesticide use, and experiment various methods to find alternative pest management techniques. They share their good practices through technical leaflets openly available online, demonstrations held at their farms, educational videos and presentation at regional or 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 methods. The program aims to provide relevant advice to farmers in order to help their transition away from pesticide use and also relies on its networking aspect to foster peer-to-peer learning within 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.[7] However, this is not sufficient evidence to judge the impact of the program, as the choice to join the network is likely to be 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 making it possible to distinguish the effects of enrolling some specific farms from the effects of the program itself.

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

[7] 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 field crops groups – polyculture and breeding DEPHY groups, 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 of 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 who 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 and therefore having the possibility of interacting informally with the direct beneficiaries of the program, to change their agricultural practices. These spillovers are particularly relevant from a policy perspective, as they can potentially multiply the impact of the program for a low additional cost.

B Appendix B

B.1 Data description

Table B.1: Characteristics of farm practices 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

C.1 Construction of the Pseudo-Panel Database

Figure C.2: Distribution of observations among regions

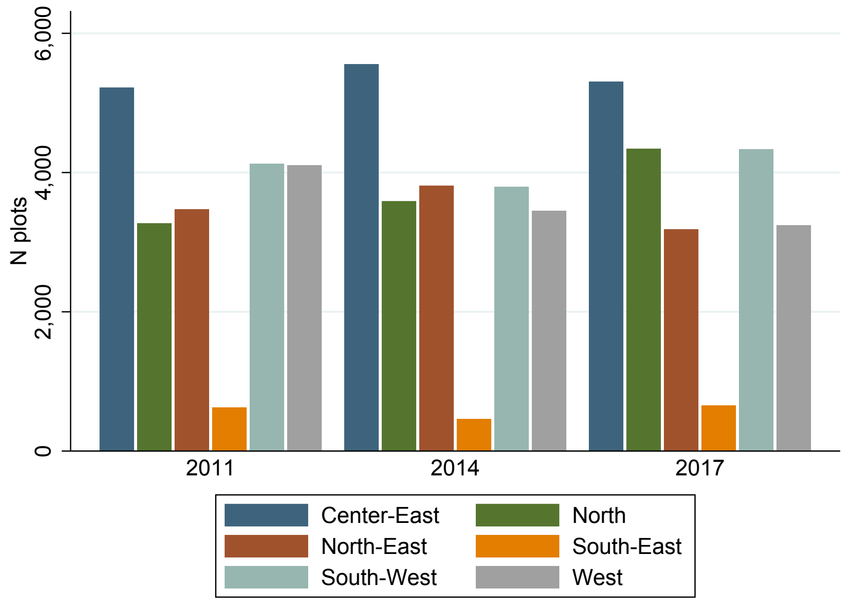


Figure C.3: Distribution of observations among crop types

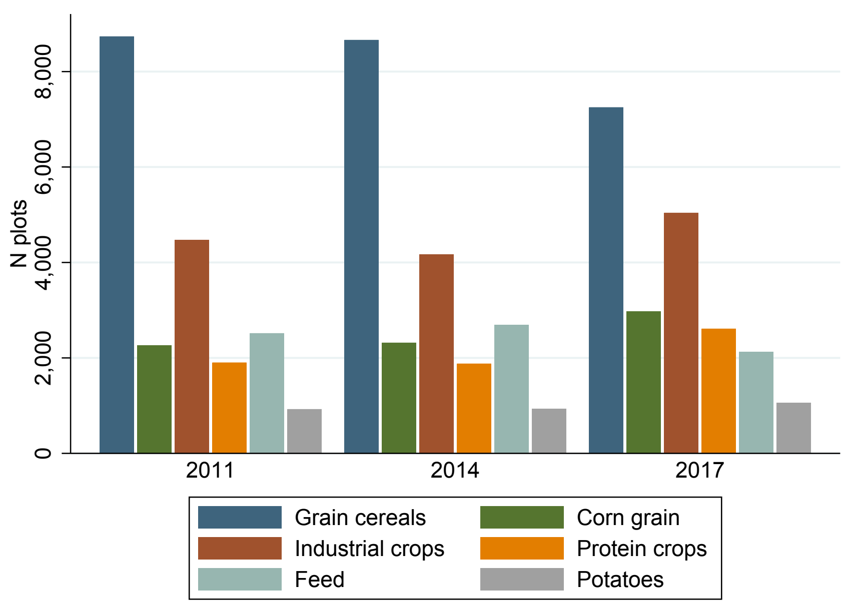


Figure C.4: Distribution of observations depending on total UAA

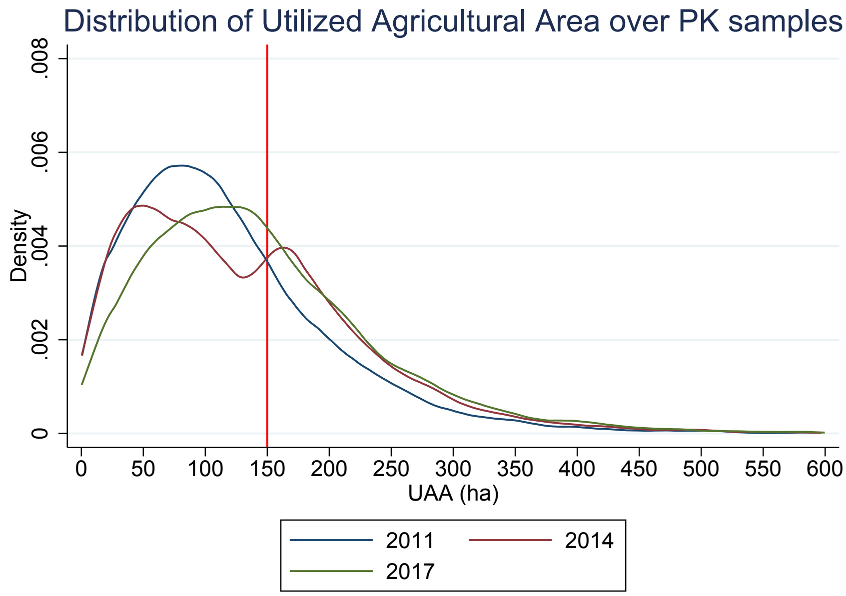
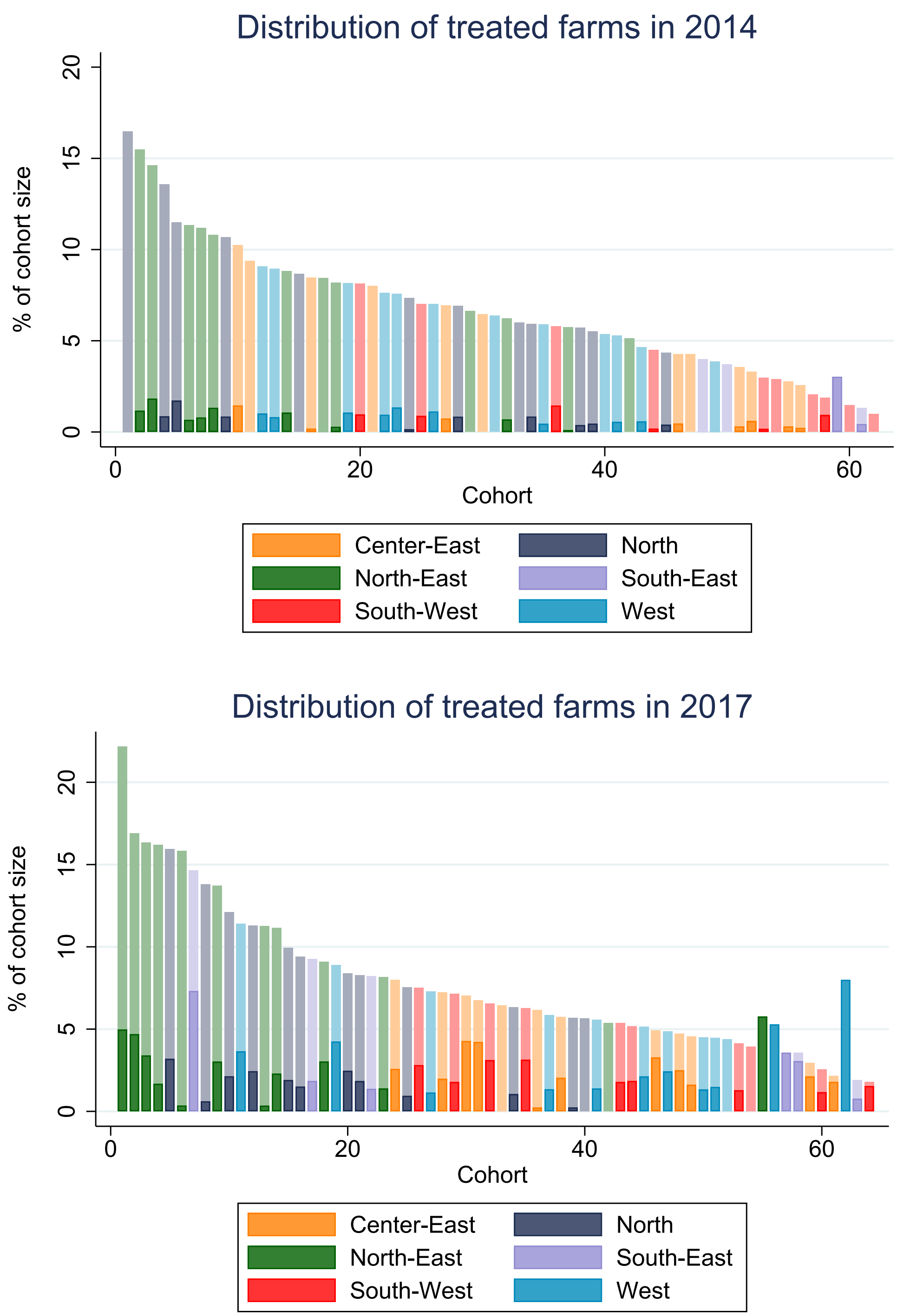
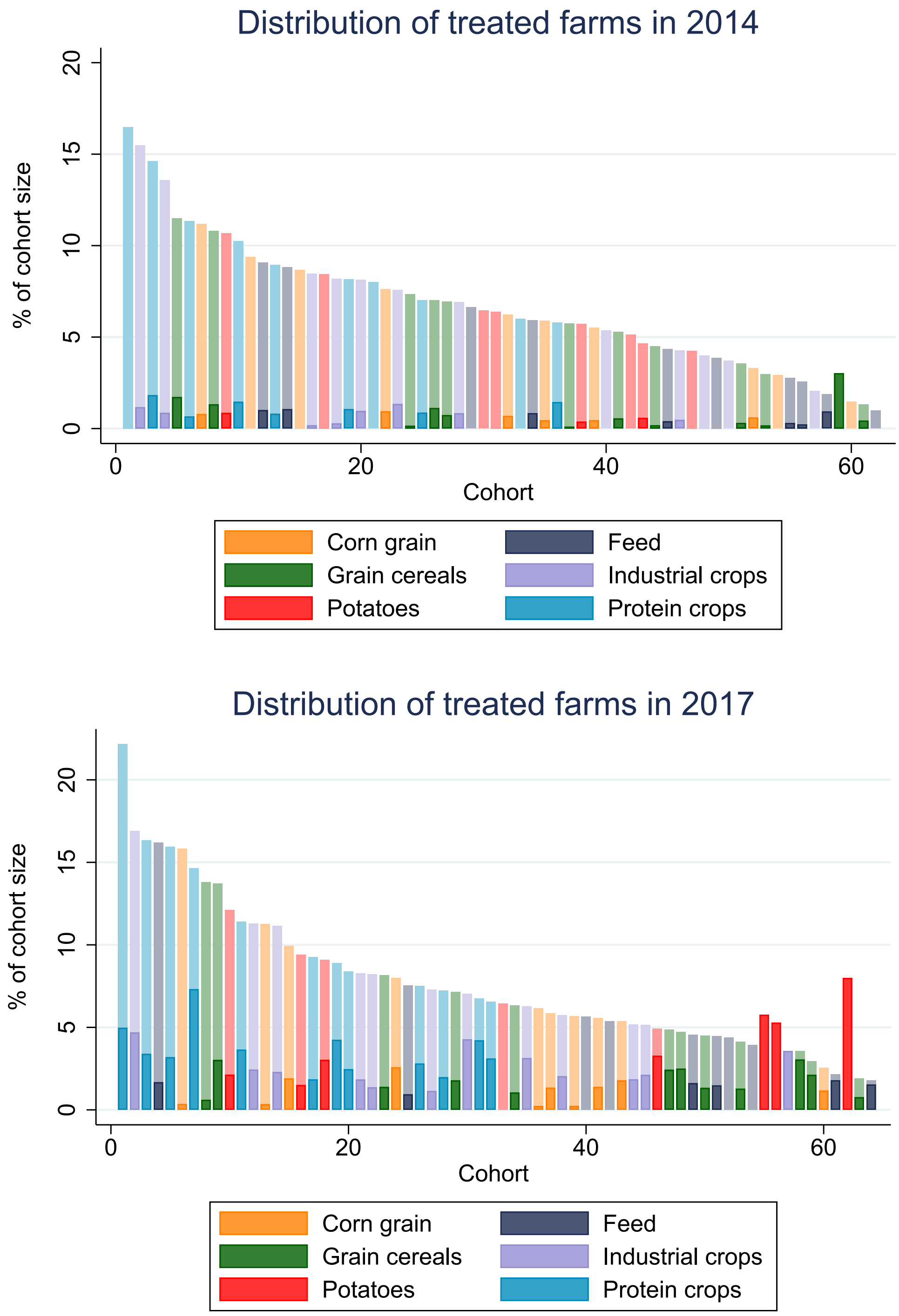


Figure C.5: Percentage of treated T1 and T2 farms in each cohort broken down by regions



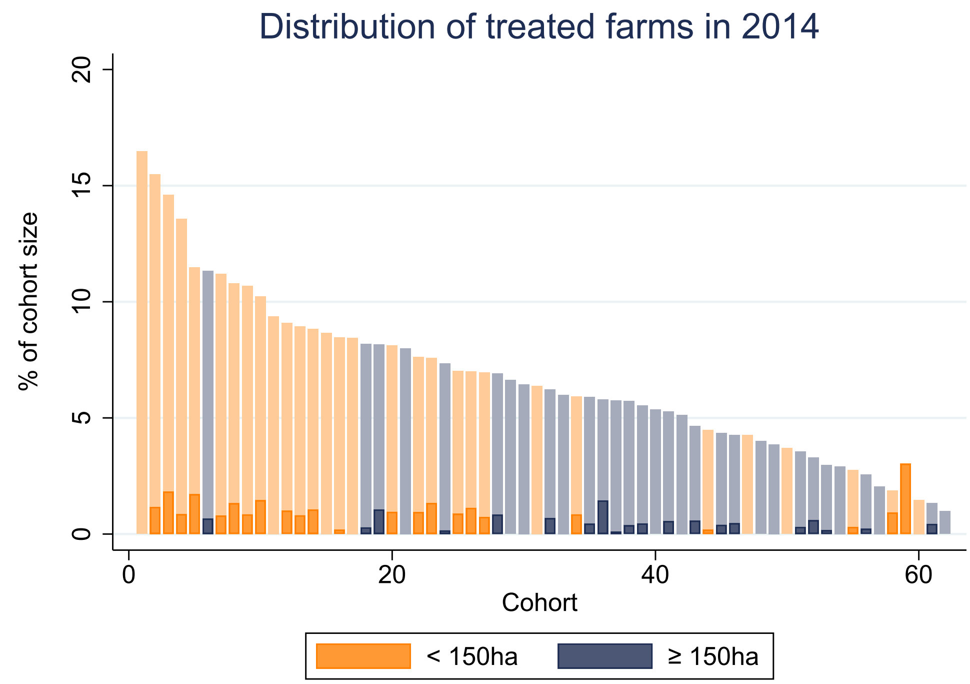
Note: The share of T1 farms is indicated by the opaque bars and the share of T2 farms in the more transparent shades.

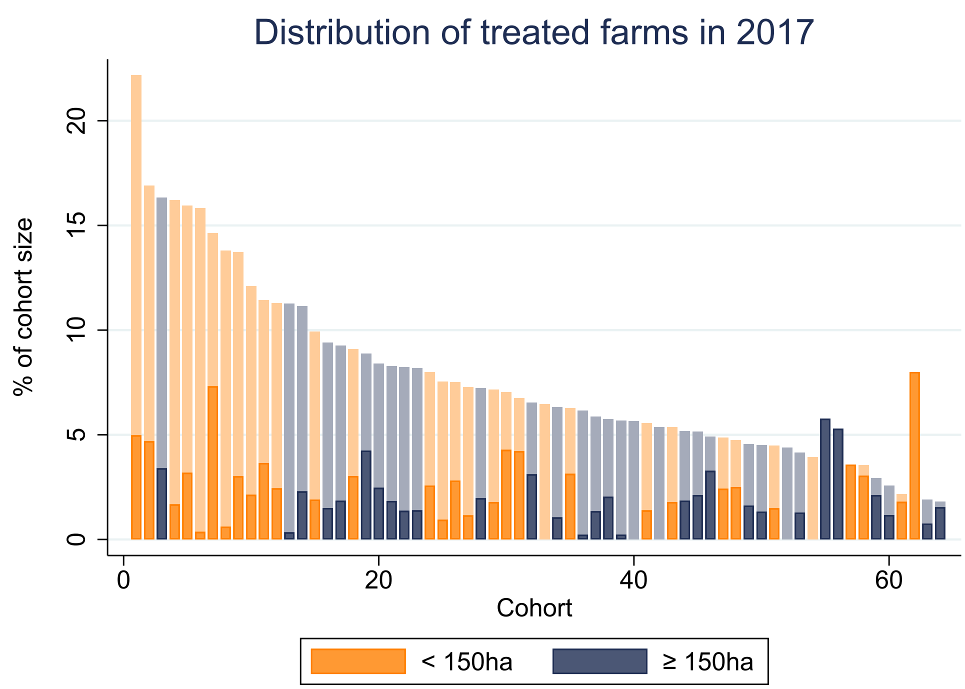
Figure C.6: Percentage of treated T1 and T2 farms in each cohort broken down by crop type



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

Figure C.7: 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 in the more transparent shades.

D Appendix D

D.1 Alternative AES control

We control for an alternative measure of enrollment in an AES, which is equal to one if the plot is in a pesticide AES for the years 2011 and 2014 and equal to one if the plot is in any AES in 2017. This measure accounts for the evolution of the definition of the schemes.

Table D.2: Pseudo panel regression of pesticide use on T1 and T2, generic AES control

	(1)	(2)	(3)	(4)
	TFI	TFI	APP	APP
T1	-0.0621***		0.0255	
	(0.0190)		(0.0208)	
T2	-0.0539**		-0.0486*	
	(0.0235)		(0.0288)	
T1 × 2014		-0.0471		0.0064
		(0.0320)		(0.0378)
T1 × 2017		-0.0730***		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
Generic AES	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
N	190	190	190	190

Notes: The dependent variables and all quantitative explanatory variables are in IHS. Reference year is 2011.

Robust Standard Errors in parenthesis.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$