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## ► To cite this version:

Margaux Lapierre, Alexandre Sauquet, Julie Subervie. Providing technical assistance to peer networks to reduce pesticide use in Europe: Evidence from the French Ecophyto plan. 2019. hal-02190979v2

**HAL Id: hal-02190979**

**<https://hal.science/hal-02190979v2>**

Preprint submitted on 13 Feb 2020

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# Providing technical assistance to peer networks to reduce pesticide use in Europe: Evidence from the French Ecophyto plan

Margaux Lapierre, Alexandre Sauquet  
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CEE-M Working Paper 2019-15

# Providing technical assistance to peer networks to reduce pesticide use in Europe: Evidence from the French Ecophyto plan

Margaux Lapierre\*    Alexandre Sauquet†    Julie Subervie‡

*(Revised version, February 2020)*

## Abstract

Can agricultural extension policies be improved by leveraging the power of peer influence? In this study, we evaluate the performance of the French Ecophyto plan aimed at reducing pesticide use, focusing on its flagship scheme, which has provided technical assistance to 3,000 volunteer pilot farms enrolled as peer groups since 2011. We use panel data collected from a representative sample of vineyards, known to be among the heaviest consumers of pesticides. We apply a variety of quasi-experimental approaches to estimate the impact of program participation on pesticide use and crop yields of enrolled vineyards. We find that participants have used 8 to 22 percent lesser pesticides than they would have used in the absence of the program. Moreover, we find that this change of practices resulted in a decrease in yields for only a fraction of enrolled peer farms, while others appear to have maintained their yields. Altogether these results suggest that providing technical assistance to peer groups can be effective in significantly reducing pesticide use in France, and presumably in developed countries more generally, for a cost per hectare that is not greater than that of the average European agri-environmental scheme.

Keywords: Agricultural extension; Developed country; Technical assistance; Farming practices; Pesticides; Treatment effects.

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

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# 1 Introduction

For 60 years now, adverse consequences of pesticides, from DDT to glyphosate, on biodiversity, water quality and human health, have constantly been revealed by scientific studies (Krebs *et al.*, 1999; Aktar *et al.*, 2009; Lai, 2017). Hence, in recent decades, programs and policies designed to reduce pesticide use have featured prominently on the European Union (EU)'s political agenda. With its particularly well-developed agricultural sector, France is the greatest user of pesticides in ton per year in Europe. In 2008, within the framework of the EU Directive on Pesticides (2009/128/EC) the French government launched the Ecophyto plan, which pledged to half the use of pesticides over the subsequent ten years allocating an annual budget of 40 to 70 million euros. Although widely criticized (Stokstad, 2018), this program has never been rigorously evaluated.<sup>1</sup> While it is clear that the drastic target of a 50 percent reduction in pesticide use had not been reached by 2018,<sup>2</sup> some components of the program may have been successful. In this paper, we evaluate the performance of the Ecophyto plan, focusing on its flagship program, the DEPHY farm network, an innovative policy that has provided technical assistance since 2011 to 3,000 volunteer pilot farms enrolled as peer groups.

Achieving ambitious levels of pesticide reduction requires profound changes in production processes. Numerous alternative forms of sustainable crop protection have been available for many years now, but only partial or step-wise adoption is typically used by farmers (Bailey *et al.*, 2009). One reason for this is that farmers have little guidance for strategically implementing alternative methods that would be applicable to their particular situation (climatic and crop specific growing conditions). In many cases, farmers are even not aware of the most advanced sustainable agricultural techniques and practices available. In such cases, providing farmers technical assistance may be critical for a successful transition to pesticide-free agriculture. Such technical assistance is precisely what the DEPHY program offers. Farmers who choose to participate are enrolled in peer groups made up of a dozen farmers who meet several times a year and to whom the government provides free technical assistance through a dedicated technical engineer. The aim of the program, offered to 1,900 farms in 2011, was to show that decreasing pesticide use while maintaining yields was a feasible objective. In 2016, the French authorities expanded the network from 1,900 to 3,000 farms.

The DEPHY program is designed to encourage information sharing within the network of enrolled farms. It provides nothing more than opportunities for peer interaction and free technical assistance, which makes it very different from previous programs that offered monetary compensation in return for adopting green practices (as in Europe, see for instance Chabé-Ferret & Subervie, 2013) or in return for retiring environmentally sensitive land from farming activity (as in US, see Feng *et al.*, 2006). On the one hand, the program offers good

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<sup>1</sup>Lechenet *et al.* (2017) reports potential achievements of DEPHY farms but does not provide any impact evaluation. For comments on the latter paper see Frisvold (2019).

<sup>2</sup>Recent figures indeed show that, overall, pesticide use actually increased in France between 2008 and 2018 (Stokstad, 2018; Hossard *et al.*, 2017; Eurostat, 2018).

prospects, since the presence of a technical expert is likely to foster a profound redefinition of the whole production process, while conditional payment programs usually target simple and marginal changes in farming practices. Furthermore, one can expect agricultural extension to be most effective in the early stages of the technology dissemination process (Anderson & Feder, 2007), which is precisely the ambition of this pilot program. Moreover, participation in a peer group might render the policy more efficient as a result of farmers' sharing of personal information and feedback with each other (Benyishay & Mobarak, 2019; Bandiera & Rasul, 2006; Conley & Udry, 2010). Indeed, collective approaches for the implementation of new techniques are often referred to as the "gold standard" for improving farming practices (Kudsk & Jensen, 2014), since they can both facilitate the identification of common problems and influence farmers' perceptions of the risks associated with alternative practices, as well as increase farmers' confidence in their ability to implement these practices (Lamichhane *et al.*, 2015). Nevertheless, doubts about the effectiveness of a program that does not impose any quantified targets to participating farms (contrary to conditional payment programs) may be justified. Moreover, previous studies are rather pessimistic on the effects of extension services, due to numerous other sources of information available to farmers (Anderson & Feder, 2007). Finally, social learning can have an ambiguous effect, since the existence of many adopters in the network may increase incentives for some to strategically delay adoption and free ride on the knowledge accumulated (Bandiera & Rasul, 2006).<sup>3</sup> Thus, judging the effectiveness of such a program requires careful empirical examination.

We estimate the impact of the DEPHY program on pesticide use and crop yields of enrolled vineyards. We focus on viticulture because since 2010 the French Ministry of Agriculture's Department of Statistics has carried out three surveys on phytosanitary practices from a representative sample of about 4,000 vineyards, providing a unique opportunity to assess the effectiveness of the DEPHY program about four years after the first-wave of farmers' enrollment. Wine growing is, moreover, the agricultural system characterized by the highest level of pesticide use per hectare (Agreste, 2012; Aka *et al.*, 2018). Distinguishing the effects of enrolling some specific farms from the effects of the program itself remains a challenge. Given that farmers were not randomly selected for participation in the DEPHY program, we combine a variety of quasi-experimental approaches to identifying the effects of the program, including matching procedures, difference-in-differences (DID) estimation, and DID-matching techniques. Using quantile regressions, we also study a possible heterogeneity in the effects of the program.

Although the number of enrolled farms that were surveyed before and after the program launched is ultimately small, we are able to accurately estimate many of its effects. Taken together, all estimates point to the same conclusion: that the DEPHY program was successful in reducing chemical pesticide use. While non-participants increased their use of pesticides between 2010 and 2016, participant farms in the DEPHY network did not record similar deteri-

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<sup>3</sup>Munshi (2004) however shows that social learning may be weaker in a heterogeneous population.

oration in their practices. In particular, we find that after 4 years in the program, participating farms use 8 to 22 percent lesser pesticides than they would have used in the absence of the program. Moreover, looking at the disaggregated indicators of pesticide use, we find that this improvement is driven by a significant decrease in fungicide use. The quantile regression results also indicate that the impact of the program does not differ significantly across quantiles, which suggests that the subset of participants under study is quite homogenous. In addition, we find that the reduction in the use of chemicals was accompanied by an increase in the use of biocontrol products ranging from 24 to 33 percent. We find that this drastic change in practices is mainly driven by the use of biocontrol products as fungicides. This effect varies slightly across participants. Finally, we find that this change of practices resulted in a reduction in yields for a fraction of enrolled farms while others seem to have maintained their yields.

This paper is broadly related to a body of research in economics that deals with public policies aimed at increasing the sustainability of agricultural systems. Whereas agricultural extension has often proven ineffective in improving farming practices (Anderson & Feder, 2007; Udry, 2010; Krishnan & Patnam, 2013), the importance of social learning has been established in a variety of contexts, including technology adoption in agriculture (Bandiera & Rasul, 2006; Conley & Udry, 2010; Foster & Rosenzweig, 1995). In particular, it has been shown that first-adopters are likely to increase the information available to other members of a network, (the so-called learning externality, Besley & Case, 1993; Conley & Udry, 2010) and that they care about how many other individuals adopt because of possible network externalities (Besley & Case, 1993). Interestingly, a number of recent papers have provided evidence that extension policies that seek to promote new technologies could be improved by leveraging the power of peer influence (Benyishay & Mobarak, 2019; Beaman & Dillon, 2018; Nakano *et al.*, 2018; Magnan *et al.*, 2015). So far, this literature has focused on the adoption of new technologies in developing countries. Our study adds to the existing literature by providing new evidence on the effectiveness of extension policies that rely on peer networks to experiment with and exchange information about new technologies in the context of developed countries. Although well below the expectations of the French government, our results are rather encouraging, as they suggest that providing technical assistance to peer networks can be effective in significantly reducing pesticide use in France, and presumably in developed countries more generally, for a cost per hectare not greater than the average European Agri-Environmental Scheme (AES).

The rest of the paper is organized as follows. Section 2 presents the European context and the DEPHY program. Section 3 presents the conceptual framework and Section 4 outlines the empirical strategy. The results of the various estimations are presented in Section 5 and discussed in Section 6. Finally, Section 7 emphasizes the policy implications of our results and provides directions for further research.

## 2 Background

### 2.1 The European context

Since the mid 1980s, a number of pesticide reduction programs have been implemented in several European countries, with mixed results (Neumeister, 2007; Gianessi *et al.*, 2009; Chabé-Ferret & Subervie, 2013; Lefebvre *et al.*, 2015; Kuhfuss & Subervie, 2018). In recent years, EU legislation has been modified, and various new regulations have been released, including restrictions on the use of certain pesticides.<sup>4</sup> Since 2009, the European Union Directive 2009/128/EC on the Sustainable Use of Pesticides (EU, 2009b) has mandated all professional pesticide users to adopt Integrated Pest Management (IPM) principles and calls has called on Member States to ensure the adoption of IPM through crop-specific guidelines.<sup>5</sup> Agricultural extension services are expected to play a central role in IPM implementation as Member States are required to provide farmers with the necessary information, tools and advisory services for adopting IPM.

### 2.2 The DEPHY program

In this context and issuing from the Grenelle consultation process on environmental issues,<sup>6</sup> the Ecophyto 2008 plan emerged with the objective of cutting nationwide use of pesticides by 50 percent in the space of ten years.<sup>7</sup> The Ecophyto plan's desired outcome has not yet been achieved, and 50 percent target has been postponed until 2025. A central component of the Ecophyto plan was the creation of the so-called DEPHY network of pilot farms that was intended to demonstrate the feasibility of the plan's objectives.<sup>8</sup> Created in 2010, the DEPHY network is constituted of local groups of a dozen farmers. Each group is supported by an engineer, who provides technical assistance for implementing cropping systems that require the use of fewer pesticides. Following a test phase that began in March 2010, 1,900

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<sup>4</sup>These restrictions relate to the maximum levels of pesticide residues in food (EU, 2005, 2009c) and to safety requirements on technologies (e.g., spraying materials) used by farmers (EU, 2009a).

<sup>5</sup>According to the definition of the US Environmental Protection Agency, IPM is not a single pest control method but, rather, a series of pest management evaluations, decisions and controls. In practicing IPM, growers who are aware of the potential for pest infestation follow a four-tiered approach: (i) set action thresholds, (ii) monitor and identify pests, (iii) use prevention methods, (iv) use control solutions.

<sup>6</sup>In 2007, France organized round tables as part of the so-called "Grenelle Environment Forum" to define the ecological and sustainable development issues that should be at the core of environmental policies in the following years (Whiteside *et al.*, 2010).

<sup>7</sup>Several studies have demonstrated that the use of pesticides is generally not optimal (Gaba *et al.*, 2016; Mailly *et al.*, 2017; Nave *et al.*, 2013), that alternatives do exist (Lamichhane *et al.*, 2015; Andert *et al.*, 2016; Petit *et al.*, 2015) and that substantial reductions in pesticide use can be achieved without impacting productivity (Babcock *et al.*, 1992; Jacquet *et al.*, 2011; Lechenet *et al.*, 2017; Frisvold, 2019).

<sup>8</sup>Other components of the French Ecophyto plan include the issuance of individual certificates for any user or distributor of plant protection products for professional purposes, the dissemination of Plant Health Bulletins (BSV) that provide reliable information on the health situation of crops thanks to field observation, and the teaching of alternative agricultural practices in agricultural public schools (EPLEFPA). The dissemination of BSV is considered as the second major component of the Ecophyto I plan, while the other tools have been more substantially developed through the Ecophyto II plan that started in 2016 (Guichard, Laurence *et al.*, 2017).



Finally, it is worth mentioning that the program's cost per hectare is not greater than most EU AES schemes designed to reduce pesticides. In 2018, the DEPHY network cost 13.5 million euros, including the salaries of technical assistants, the cost of data treatment and administrative and management costs (Brun, 2019). The vineyards within the 3,000 farms of the network engaged on average about 30 hectares in the program, which gives us a cost of 150 euros per ha and per year.<sup>10</sup> As a comparison, the AES payment to reduce herbicides in French vineyards from 2007 to 2014 ranged from 141 euros per ha and per year to 350 euros per ha and per year (Kuhfuss & Subervie, 2018).

## 3 Conceptual framework

### 3.1 The decision to reduce pesticide use

The program attracts farmers who are willing to opt for non-conventional farming. Since a number of alternative forms of sustainable crop protection have been available for some years now, these farmers can access at least some of the information necessary for the implementation of these new techniques. In practice, farmers can use various sources of information, which include members of their cooperative, farmers in their watershed, input suppliers, and ONVAR facilitators.<sup>11</sup> The DEPHY program constitutes an additional source of information for these farmers.

The level of pesticide use of a farmer depends in particular on the available information on alternative forms of sustainable crop protection. The way a farmer processes the available information varies, depending on whether he participates in the DEPHY program or not (Lin, 1991). The effectiveness of the program, namely the gain from moving the farmer from the state “without DEPHY program” to the state “with DEPHY program”, depends on the relative effectiveness of DEPHY in inducing significant changes in practices compared to other available sources of information.

### 3.2 Parameters of interest

Our objective is to estimate the causal effect of participation in the DEPHY program on the amount of pesticides used by participants or the Average Treatment Effect on the Treated (ATT). The ATT is defined as the mean difference between the level of the outcome considered (here the level of pesticide use or the yield) among vineyards in the DEPHY network and what

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<sup>10</sup>This is a back-of-the-envelope calculation intended to provide the reader with an idea of the order of magnitude.

<sup>11</sup>ONVAR refers to Organisme National à Vocation Agricole et Rurale, the French name for the various organizations that aim to shift agricultural practices towards agroecology, by revitalizing the links between farmers and the variety of stakeholders involved in the agroecological transition.

this level would have been in the absence of the program (the counterfactual scenario):

$$ATT = E[Y^1 - Y^0 | D = 1] = \underbrace{E(Y^1 | D = 1)}_{\text{observable}} - \underbrace{E(Y^0 | D = 1)}_{\text{unobservable}}$$

where  $Y^1$  is the level of the outcome in the presence of the DEPHY program,  $Y^0$  is the level of the outcome in the absence of the program and  $D$  is the treatment variable that is equal to 1 for DEPHY winegrowers and 0 otherwise. Since the counterfactual level  $E(Y^0 | D = 1)$  is not observable, it must be estimated. To do this, we follow a quasi-experimental approach that uses non-participating farms to construct valid control groups.

## 4 Empirical strategy

### 4.1 Data sources

We used the 2010 agricultural census to gather information on socio-economic and production characteristics of farms before the program began. Moreover, we used two sources of data on the phytosanitary practices of vineyards: three national surveys carried out by the French Ministry of Agriculture (MA)'s Department of Statistics and the Agrosyst database that describes the cropping systems implemented on DEPHY farms and documents their development over time. The surveys were run in 2010, 2013, and 2016 on a sample of 9,369 wine farmers who were each interviewed at least once about their practices on randomly chosen parcels. Among these, 3,984 parcels were investigated in the three surveys. The Agrosyst database also records all phytosanitary product applications of DEPHY vineyards at the cropping system level, from 2011 to 2016.<sup>12</sup>

We used the Agrosyst data in two ways. First, we matched the Agrosyst database to the national surveys to determine how many DEPHY farms had been surveyed in 2010, 2013 and/or 2016. We combined these two databases on the basis of a common identifier (the farm business identification number) and found that 182 DEPHY farms had been surveyed at least once in 2010, 2013, or 2016. Most of them (63 percent) enrolled in the program in 2011 or 2012, while the others enrolled much later (in 2016). In our analysis, we thus distinguish early participants from second-wave participants. We ended up with 45 farms from the first-wave of participants and 36 farms from the second-wave of participants who were each surveyed three times. Second, we used the Agrosyst database to gather information on the use of phytosanitary products by all the DEPHY vineyards (not only those that appeared in the national surveys). In particular, we were able to retrieve comprehensive information on phytosanitary product use in 2016 for 124 of the 207 cropping systems that entered the DEPHY network between 2011 and 2012 (first-wave participants).

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<sup>12</sup>A cropping system is a series of homogeneously managed plots, i.e., all organic vineyards, or all those under a common certification designation.

As the DEPHY program began in 2011, data on the phytosanitary practices measured in the 2010 survey are considered as pre-treatment outcomes, while data on the phytosanitary practices measured in the 2016 survey can be considered as post-treatment outcomes. Technically, data on the phytosanitary practices measured in the 2013 survey should be seen as post-treatment outcomes as well, although the time required to implement new farming techniques makes effects of the program unlikely to be detected at this early stage. Note that we do not have post-treatment data on phytosanitary practices for farms enrolled during the second wave of participation in the program. Consequently, these farms are considered as untreated in our framework. They can, however, be used to test our identification strategy, as we will see in the following section.

## 4.2 Pesticide use and yields

The MA surveys and Agrosyst database provide information on the quantity of pesticides used by winegrowers on the surveyed parcels, as measured through the Treatment Frequency Index (TFI). This index represents the number of so-called reference doses of pesticides applied during a farming year.<sup>13</sup> The reference dose is often considered the normal dose, as it corresponds to the efficient dose of a product for a specific culture and pest:

$$\text{TFI} = \sum \frac{\text{applied dose}}{\text{reference dose}} * \frac{\text{treated area}}{\text{total area}}.$$

For example, if the reference dose of an herbicide is spread over the entire area of a plot, then the TFI of the plot equals one. If the herbicide is spread at its reference dose but only under the vine rows, the TFI of the plot equals one-third, because the space between vine rows is roughly twice as wide as the vine row itself (Kuhfuss & Subervie, 2018). The annual TFI of the entire parcel is the sum of the TFI calculated for each treatment carried out on the parcel during a crop season. The MA surveys provide a range of disaggregated indicators, including the Herbicide TFI, the Insecticide TFI, the Fungicide TFI and the Total TFI.<sup>14</sup> Moreover, each TFI can be disaggregated so that the chemical compounds can be distinguished from the biocontrol compounds.

Table 1 reports the average value of the TFI for DEPHY and non-DEPHY farms in 2010, 2013 and 2016, as provided by the MA surveys and the Agrosyst database. It also reports mean values of the yield as measured by the amount of wine (in hectoliters) that is produced per hectare of vineyard. Table 1 calls for three observations. First, looking at participating farms for which two values of the TFI are provided, we note that the average value of the chemical TFI computed from Agrosyst data (11.14) is lower than that provided by the MA

<sup>13</sup>In viticulture, the 2010 crop year begins after the harvest in September 2009 and ends with the harvest in September 2010.

<sup>14</sup>Herbicides, insecticides and fungicides are the main components of the total TFI; a few sanitary products concern other pests such as acarids.

surveys (11.96). This is consistent with the fact that the TFI recorded in the surveys does not systematically reflect the practices used on the parcel enrolled in the program, but could reflect the practices used on another parcel of the farm, one that is likely farmed under a conventional cropping system and therefore a higher TFI.<sup>15</sup> Second, the use of biocontrol products increases over time in both groups – from 0.77 to 2.27 among participants and from 1.17 to 2.11 among non-participants – which suggests a general tendency towards improved farming practices over the period. Third, DEPHY farms and non-DEPHY farms differ in many ways. The use of pesticides is different across groups throughout the period, especially in 2016, when DEPHY farms have a significantly lower TFI (11.96) than non-DEPHY farms (14.2) according to MA surveys. The use of biocontrol pesticides is different across groups as well in 2016, when, the TFI equaled 2.27 among DEPHY farms versus 2.11 among non-DEPHY farms. Also, DEPHY farms recorded lower yields in 2016 (43.47 hl per ha) than non-DEPHY farms (54.1 hl per ha).<sup>16</sup> Our goal is to assess the extent to which these gaps can be attributed to the program.

Table 1: Treatment Frequency Index (TFI) and yields: Descriptive statistics by group

	non-DEPHY farms (from MA surveys)		DEPHY farms (from MA surveys)		DEPHY farms (from Agrosyst)	
	Obs.	Mean	Obs.	Mean	Obs.	Mean
Chemical pesticide use						
TFI in 2010	3957	12.13	45	11.02	n.a	n.a
TFI in 2013	3957	14.07	45	12.02	n.a	n.a
TFI in 2016	3957	14.2	45	11.96	124	11.14
Biocontrol pesticide use						
TFI in 2010	3957	1.17	45	0.77	n.a	n.a
TFI in 2013	3957	1.6	45	1.89	n.a	n.a
TFI in 2016	3957	2.11	45	2.27	123	4.2
Yields (hl per ha)						
Yields in 2010	3957	64.87	45	61.23	n.a	n.a
Yields in 2013	3957	59.12	45	53.35	n.a	n.a
Yields in 2016	3957	54.1	39	43.47	64	61.60

Note: This table provides the mean value of the TFI and the yields in the two groups as computed from the two sources of data, namely the surveys run by the French Ministry of Agriculture and the Agrosyst database.

<sup>15</sup>Although 70 percent of the DEPHY farms identified in the MA surveys enrolled 100 percent of their utilized agricultural area (UAA) in the program.

<sup>16</sup>Agrosyst data shows similar differences between groups except for yields (see also Figures A1, A2, and A3). We come back to this point in Section 5.4 and 6.

### 4.3 Winegrower characteristics

Winegrower characteristics are taken from the French Agricultural Census that was conducted in 2010 by the Ministry of Agriculture. The census data contains detailed descriptions of French farmers from the 2009-2010 farming year, i.e., before the DEPHY program began. Specifically, it provides information on a range of agronomic, social and economic variables likely to influence both the use of pesticides and the decision to participate in the DEPHY program, including the characteristics of the farm (land use, labor force, insurance, diversification activities, ownership), the head of the farm (age, sex, education, spouse's main activity), the production of the farm (quantity of wine produced, quality labels, sales), and the farming practices employed (spraying of pesticides, land area without pesticides, organic farming, if any). To this data we added two more pieces of information from the MA survey and Agrosyst database: whether the plot is cultivated as organic and the wine-growing basin of the plot (Burgundy, Bordeaux,...). This latter information is very important since pest pressure and diversity vary greatly depending on which area of France a parcel is located.

Table 2 provides summary statistics for the DEPHY farms (referred to in the Table as participants) and the non-DEPHY farms (referred to as non-participants) in 2010. DEPHY farms are larger on average, they calibrate their pesticide sprayer more often and sell their wine in short circuits. The head of a DEPHY farm is more likely to have a bachelor's degree, be a member of a farmers' organization, and diversify his farming activities, indicating that the DEPHY program attracts a particular type of farmer.<sup>17</sup>

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<sup>17</sup>Note also that the subset of DEPHY vineyards that appears in the MA surveys significantly differs from the whole sample of DEPHY vineyards since it includes farms that are larger on average (75 ha) than the average DEPHY farm (32 ha). This difference is due to the sampling design of the MA surveys, where larger farms, having a greater number of plots, have greater chances of being drawn and surveyed.

Table 2: Main characteristics of farms: Descriptive statistics by group

Variable	Unit	Untreated			Treated		
		Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
On-farm labor	annual work units	6105	5322.01	18661.60	161	5548.76	5609.00
Climate insurance	yes=1	6105	0.49	0.50	161	0.50	0.50
Share of sales in short circuit	%production	6105	0.48	0.50	161	0.67	0.47
Vineyard surface area	area	6105	3116.50	6225.12	161	3208.81	4069.06
Diversification of activities	yes=1	6105	0.17	0.38	161	0.26	0.44
Calibration of pesticide sprayer	yes=1	6105	0.30	0.46	161	0.37	0.48
Gender of head of the farm	1=men, 2=women	6105	1.16	0.37	161	1.17	0.38
Year of birth of head of the farm	year	6105	1961.89	10.39	161	1965.15	8.81
Head of the farm has bachelor's degree	yes=1	6105	0.53	0.50	161	0.73	0.44
Spouse has agricultural activity	yes=1	6105	0.28	0.45	161	0.35	0.48
Spouse has non-agricultural activity	yes=1	6105	0.27	0.44	161	0.28	0.45
Wine production	hectoliters per area	6105	0.57	0.70	161	0.51	0.25
PDO and PGI production	%production	6105	0.85	0.32	161	0.85	0.32
Utilized agricultural area (UAA)	ares	6105	4990.58	7639.53	161	4372.24	5073.53
Collective management of the farm	yes=1	6105	0.63	0.48	161	0.80	0.40
UAA without pesticides	%UAA	6105	0.15	0.27	161	0.18	0.33
UAA under organic farming	%UAA	6105	0.06	0.22	161	0.12	0.30
Surveyed plot is cultivated as organic*	yes=1	6105	0.07	0.26	161	0.16	0.36

Note: This table provides the mean value of the main characteristics in the two groups as computed from the census run by the French Ministry of Agriculture in 2010. Only the variable with an asterisk (\*) is from the 2010 Farm Practices survey. "Treated" refers to Dephy farms for which we were able to compute yields or TFI from the Agrosyst database in 2016. "Untreated" refers to non-Dephy farms for which we were able to compute yields or TFI from the MA survey in 2016.

## 4.4 Estimators

To estimate the ATT in 2016, we first apply the Difference-In-Difference (DID) treatment effect estimator, which is commonly used in evaluation work and measures the impact of the program intervention by comparing the difference between pre- and post-intervention outcomes across the treated and untreated groups (Todd, 2007).<sup>18</sup> In practice, we regress the change in the outcome between 2010 and 2016 on the treatment variable  $D$ , using first-wave participants as the treated group and non-participants as the untreated group.

Using DID requires a parallel trend assumption, which assumes that in the absence of the treatment, the difference between the treated and the untreated groups would have been constant over time. In the present study, this assumption can be tested using a placebo test that applies the DID estimator to the change in the outcome between 2010 and 2016 among second-wave participants, for whom no effect should be detected over this period (since they were not yet participants). If the testing procedure fails to reject the null hypothesis of no impact, we would conclude that the parallel trend assumption holds. If the testing procedure rejects the null hypothesis, this could be interpreted as an anticipation effect, suggesting that the program has an effect even before it has begun (Chabé-Ferret & Subervie, 2013). Thus, if it is possible to rule out an anticipation effect among second-wave participants, rejection of the null hypothesis could be interpreted as weakening the evidence for the parallel trend assumption (Imbens & Wooldridge, 2009).

Following Ferraro & Miranda (2017) and Haninger *et al.* (2017), we use the DID-matching estimator, which tackles the issue of self-selection in two steps: first, it deals with selection on observables by comparing treated farms and untreated farms that have the same observable characteristics  $X$  before the program begins; second, it addresses selection on time-invariant unobservables by subtracting the difference in the pre-treatment outcomes from the difference in the post-treatment outcomes between the two groups. Therefore, the DID-matching estimator essentially compares changes in the outcomes over 2010-2016 between first-wave participants and their  $X$ -matched untreated counterparts. The set of observable factors  $X$  includes a large range of variables extracted from the 2010 census and displayed in Table 2. This strategy allows us to perform an exact matching procedure on the wine-growing basins, which ensures that control and treated parcels are subject to similar agronomic and meteorological constraints, a very important condition when dealing with agricultural outcomes.

Remember that the TFI information recorded in the MA surveys does not necessarily reflect the practices implemented on the parcel enrolled in the DEPHY program and could instead re-

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<sup>18</sup>This identification strategy relies on the stable unit treatment value assumption (SUTVA), which implies here that the practices of non-participants have not been altered by the DEPHY program (Rubin, 1978). Although we cannot exclude the possibility that some DEPHY winegrowers had shared their experiences and results with non-DEPHY winegrowers, it is reasonable to assume that any sharing of experience would have been insufficient to modify the practices of non-DEPHY farms at this stage of the program. Knowledge transmission outside of the network was indeed one objective of the Ecophyto plan, but only became a central aspect of the plan with the launch of Ecophyto II in 2016.

flect the practices of another parcel on which no special effort was made to reduce chemical pesticides. Using these data in a DID(-matching) estimation is thus likely to lead to underestimation of the impact of the program on the TFI levels of participating farms. As such, the estimate produced by the DID(-matching) approach should be considered a lower-bound estimate of the program's impact.

We then turn to the Agrosyst data, which accurately reflect the phytosanitary practices implemented by the enrolled farms on the enrolled plots. Since the dataset do not provide information about the phytosanitary practices implemented by the enrolled farms during the pre-treatment year 2010, the DID approach cannot be applied to these data. We thus opt for a simple matching approach, which relies on the selection on observable assumption.<sup>19</sup> In practice, we compare the level of the outcome in 2016 of first-wave participants and their  $X$ -matched untreated counterparts, using the Agrosyst data to compute 2016 outcome levels among treated farms and the MA surveys to compute 2016 outcome levels among untreated farms. This can be done through a harmonization of TFI formulas in both datasets (see details at the end of the Appendix).

Running simple matching estimates is likely to lead to overestimation of the impact of the program on participants' TFI since the DID-matching approach usually outperforms the simple matching approach, meaning that the simple matching estimates may suffer from a (positive) selection bias. In this case, the estimate generated by the simple matching approach would reflect the upper bound of the impact of the scheme. Therefore, using both methods (DID-matching using MA surveys and simple matching using DEPHY reports) enables us to provide the likely bounds of the effects of the DEPHY program.

The heterogeneity of DEPHY farms, as shown by the standard deviations of the variables in Table 2, suggests that the impact of the program may vary across participants. In this case, examining the quantile treatment effects would make sense. The final sample used for the evaluation of the program using DID approaches is inevitably much smaller than the original sample. Indeed, this sample is too small to explore the potential heterogeneity of program impacts. However, we can do so using cross-sectional Agrosyst data, which tells us about the practices of most program participants.

## 5 Results

### 5.1 Preliminary tests

We first check the parallel trend assumption using a placebo test that applies the DID and DID matching estimators to the change in the outcome over the 2010-2016 period among second-wave participants, for whom no effect should be detected. Results are reported in Table A1 in the Appendix. In all cases, the null hypothesis of no impact cannot be rejected at the

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<sup>19</sup>The validity of the simple matching estimator also relies on the common support assumption and the SUTVA.

standard significance level. This tends to support the validity of our identification strategy for generating a lower-bound estimate of the impacts of the program. One concern with second-wave participants is that they come from a different population than first-wave participants. To test this assumption, we compare pre-treatment characteristics of both groups. Results are provided in the Appendix Table A2. They show that both groups are statistically similar, which tends to support the validity of the placebo test.

Next, we compare the degree of balance between the treated and untreated groups before and after the matching procedure for each sample when applying the DID-matching estimator and the simple matching estimator. To do so, we calculate the normalized difference between the two groups for each pre-treatment covariate  $X$ . The normalized difference is the difference in means divided by the square root of the sum of variances for both groups, which is the most commonly accepted diagnostic used to assess covariate balance (Rosenbaum & Rubin, 1985). Tables A3, A4, A5, and A6 in the Appendix provide the results of the balancing tests for our preferred estimator, the nearest neighbor estimator based on Mahalanobis distances. Since the normalized difference is considered negligible when it is below the suggested rule of thumb of 0.25 standard deviations (Imbens & Wooldridge, 2009), we conclude, in all cases, that the matching procedure was successful in constructing a valid control group.

## 5.2 Impacts on chemical product use

Table 3 reports our estimates of the impact of the program on the use of chemical products by first-wave participants during the 2016 crop year. The ATT represents the difference between the TFI among participant farmers in 2016 and the TFI they would have obtained had they not participated. In all cases, the impact of the program on the total TFI is estimated with precision. The DID (resp. DID-matching) estimate suggests a significant decrease of about 1.12 points (resp. 2.73 points) in the total TFI, as shown in Col.5 (resp. Col. 3). Moreover, the simple matching estimate of the ATT indicates that the decrease in the TFI due to the program should not be larger than 3.28 points (Col. 1).

Taken together, these results suggest that the likely impact of the program ranges between 8 and 22 percent.<sup>20</sup> Examining the disaggregated TFI, we find that decrease in TFI is driven by a significant decrease in the fungicide TFI in particular. This has important consequences since fungicide is the main source of pesticide used in winegrowing, contributing to 85 percent of the total TFI. Finally, the quantile regression results indicate that the impact of the program does not differ significantly across quantiles, as shown in Figure 2, which suggests that participants react similarly to the program whatever their level of pesticide use. This finding indicates that our estimates may not be driven by outliers.

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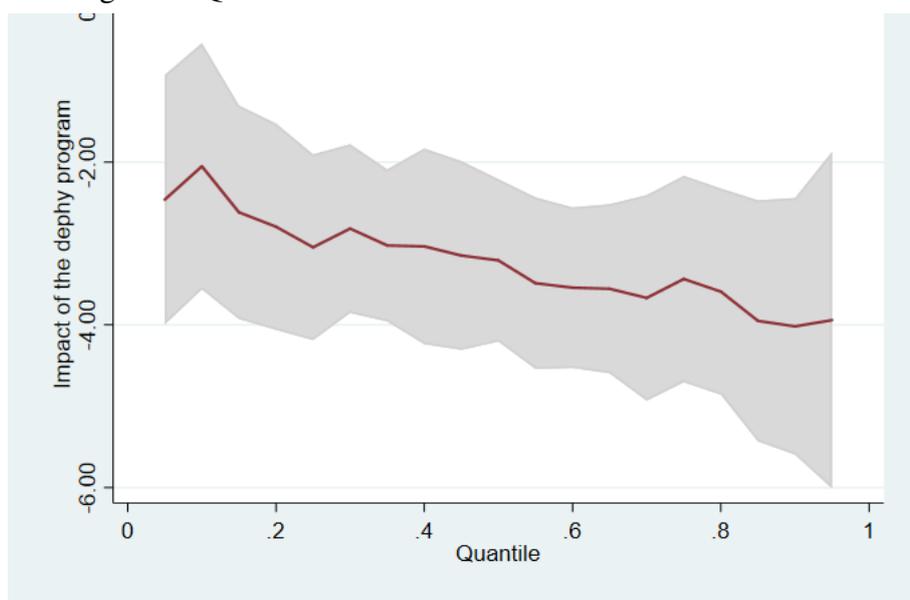
<sup>20</sup>This impact is expressed as a percentage of the estimated counterfactual TFI, which equals 13.08 points (11.96 + 1.12) using the DID approach and 14.72 points (11.44 + 3.28) using the simple matching approach.

Table 3: Impact on chemical product use in 2016

	Simple Matching		DID-matching		DID	
	ATT	(2) $Y_1$	(3) ATT	(4) $Y_1$	(5) ATT	(6) $Y_1$
Herbicides	-0.08 0.10	0.64	-0.14 0.15	0.45	-0.21 0.096	** 0.46
Fungicides	-2.49 0.46	*** 9.62	-2.80 0.97	*** 10.83	-0.87 0.71	10.34
Insecticides	-0.31 0.12	** 1.07	0.09 0.34	1.31	-0.13 0.22	1.07
All products	-3.28 0.54	*** 11.44	-2.73 1.11	** 12.70	-1.12 0.76	‡ 11.96
$n_1$	107		35		45	
$n_0$	3852		2142		3939	

Note: This table provides the results of the estimates of the impact of the DEPHY program on the TFI in 2016 among treated farms, using three different estimators. ATT refers to the average treatment effect on the treated units. Robust standard-errors are in parentheses below the coefficients.  $Y_1$  is the mean value of the TFI of the surveyed plots in the treated group. DID-matching and simple matching estimators rely on a Mahalanobis-distance-matching procedure based on the best matched untreated unit for each treated unit.  $n_1$  (resp.  $n_0$ ) refers to the number of treated (resp. untreated) units in the sample. Dependent variables for DID and DID-matching estimates rely on survey data (where the plots considered are not necessarily enrolled in the program). Dependent variables for simple matching estimates rely on DEPHY data (where the plots considered are enrolled in the program). \*\*\*, \*\*, \*, and ‡ denote rejection of the null hypothesis of no impact at the 1%, 5%, 10% and 15% significance levels, respectively.

Figure 2: Quantile treatment effects on chemical TFI in 2016



Source: Authors using Agrosyst and MA surveys data

### 5.3 Impacts on the use of biocontrol products

Table 4 reports estimates of the impact of the program on first-wave participants' use of biocontrol products during the 2016 crop year. Here again, the impact of the program on the total TFI is estimated with precision in all cases. The DID (resp. DID-matching) estimate suggests a significant increase of about 0.56 points (resp. 0.71 points) in the total TFI, as shown in Col.5 (resp. Col. 3). The simple matching estimate of the ATT indicates moreover that the decrease in the TFI due to the program should not be larger than 0.80 (Col. 1). This indicates that the program triggered an increase in the use of biocontrol products of at least 24 percent among participants.<sup>21</sup>

Turning to the disaggregated TFI, the results show that this drastic change in practices is mainly driven by biocontrol products used as fungicides.

<sup>21</sup>This impact is expressed as a percentage of the counterfactual TFI estimate, which equals 1.71 points (2.27 – 0.56) using the DID approach.

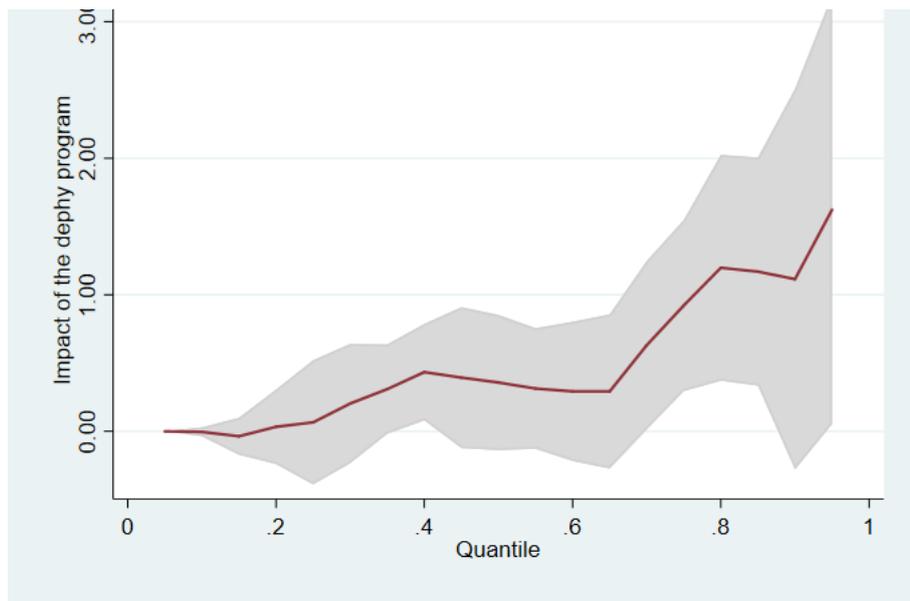
Table 4: Impact on biocontrol product use in 2016

	Simple Matching		DID-matching		DID	
	(1)	(2)	(3)	(4)	(5)	(6)
	ATT	$Y_1$	ATT	$Y_1$	ATT	$Y_1$
Fungicides	0.68 ‡	3.94	0.89 **	2.36	0.53 *	2.09
	0.46		0.37		0.31	
Insecticides	-0.01	0.00	-0.18	0.23	0.03	0.18
	0.01		0.18		0.07	
All products	0.80 *	4.08	0.71 **	2.59	0.56 *	2.27
	0.46		0.33		0.29	
$n_1$	105		35		45	
$n_0$	3852		2142		3939	

Note: This table provides the results of the estimates of the impact of the DEPHY program on the biocontrol TFI in 2016 among treated farms, using three different estimators. ATT refers to the average treatment effect on the treated units. Robust standard-errors are in parentheses below the coefficients.  $Y_1$  is the mean value of the TFI of the surveyed plots in the treated group. DID-matching and simple matching estimators rely on a Mahalanobis-distance-matching procedure based on the best matched untreated unit for each treated unit.  $n_1$  (resp.  $n_0$ ) refers to the number of treated (resp. untreated) units in the sample. Dependent variables for DID and DID-matching estimates rely on survey data (where the plots considered are not necessarily enrolled in the program). Dependent variables for simple matching estimates rely on DEPHY data (where the plots considered are enrolled in the program).\*\*\*, \*\*, \*, and ‡ denote rejection of the null hypothesis of no impact at the 1%, 5%, 10% and 15% significance levels, respectively.

Finally, Figure 3 that displays the quantile regression results shows that the effect is driven by the biggest users of biocontrol products.

Figure 3: Quantile treatment effects on biocontrol TFI in 2016



Source: Authors using Agrosyst and MA surveys data

## 5.4 Impacts on yields

Table 5 reports estimates of the program's impact on the yields of first-wave participants in 2016. The two DID estimators converge, suggesting a decrease in yields by 19 to 22 percent. The Matching estimator (Col. 1) leads to a different conclusion: that the DEPHY program did not have any significant impact on yields (coefficient non significantly different from 0).

Table 5: Impact on yields in 2016

	Simple Matching		DID-matching		DID		
	(1)	(2)	(3)	(4)	(5)		(6)
	ATT	$Y_1$	ATT	$Y_1$	ATT		$Y_{-1}$
Yield	5.24	64.50	-8.68	* 37.44	-10.47	***	43.47
	3.66		4.82		3.85		
$n_1$	47		27		39		
$n_0$	2485		1527		3137		

Note: This table provides the results of the estimates of the impact of the DEPHY program on the yields in 2016 among treated farms, using three different estimators. ATT refers to the average treatment effect on the treated units. Robust standard-errors are in parentheses below the coefficients.  $Y_1$  is the mean value of the TFI of the surveyed plots in the treated group. DID-matching and simple matching estimators rely on a Mahalanobis-distance-matching procedure based on the best matched untreated unit for each treated unit.  $n_1$  (resp.  $n_0$ ) refers to the number of treated (resp. untreated) units in the sample. Dependent variables for DID and DID-matching estimates rely on survey data (where the plots considered are not necessarily enrolled in the program). Dependent variables for simple matching estimates rely on DEPHY data (where the plots considered are enrolled in the program).\*\*\*, \*\*, \*, and † denote rejection of the null hypothesis of no impact at the 1%, 5%, 10% and 15% significance levels, respectively.

The discrepancy between the conclusions of the two estimators calls for further investigation. The source of data for yields in 2016 in the treated group are different. Looking at the distribution of yields in the two databases for the treated group is illuminating. Figure A4 in the Appendix, shows that even if the general distribution is similar in the Agrosyst and MA surveys data, there are no yields below 30 HL/ha in the Agrosyst database. Combined with the fact that numerous data on yields are missing in the Agrosyst database (information available for only 47 farms), we suspect that the database does not contain cases of very low yields observed in the program. By chance, in this project we evaluate the impact of the program using two different sources of data: one that is built from the data collected by the program's technical engineers (Agrosyst) and the other from regular surveys conducted by the Ministry of Agriculture (MA surveys). Available information indicates that even if a fraction of farms maintained yields, some suffered severe losses, thus leading us to find a negative impact of the DEPHY program on yields in the DID regressions.

## 5.5 Early impacts of the program

Next, we use data on phytosanitary practices as measured in the 2013 survey to test for the presence of impacts that materialize at an early stage of participation in the program. Table 6

reports the results of the DID estimates. Quite surprisingly, we do find a significant negative impact of the program on the use of chemical insecticides and a significant positive impact on the use of biocontrol insecticides and fungicides in 2013, although similar effects were not detected for fungicide use in 2016 (see Section 5.2). By contrast, we fail to detect any significant impact on the use of chemical fungicides in 2013 (although we do find significant impacts for the year 2016). These results very likely have to do with the experimental protocol implemented by the DEPHY technicians as part of the program and suggest that switching from chemical to biocontrol products involves a process of trial and error. Another potential explanation is that the types of pest pressure differed in 2013 and 2016.

Table 6: Early impacts of the program (ATT in 2013)

Outcomes	(1) ATT	(2) $Y_1$
<b>Chemical (TFI)</b>		
Herbicides	0.00 (0.09)	0.51
Fungicides	0.37 (0.56)	10.94
Insecticides	-0.19 * (0.1)	0.85
All products	0.17 (0.61)	12.3
<b>Biocontrol (TFI)</b>		
Fungicides	0.53 * (0.28)	1.81
Insecticides	0.11 * (0.06)	0.23
All products	0.64 ** (0.31)	2.04
Yield (hl/ha)	-1.91 (1.87)	50.7

Note: This table provides the estimates of the effects of the DEPHY program on the TFI and yield in 2013 among treated units, using the DID estimator. ATT refers to the average treatment effect on the treated units. Robust standard errors are in parentheses below the coefficients.  $Y_1$  is the mean value of the outcome of the surveyed plots in the treated group. In all estimates the sample size is 4,819, including 62 treated units. DID estimates rely on survey data (where the plots considered are not necessarily enrolled in the program). Asterisks \*\*\*, \*\*, and \* denote rejection of the null hypothesis of no impact at the 1%, 5% and 10% significance levels, respectively.

## 6 Discussion

As in many empirical studies, our findings are to some extent specific to the period analyzed. As such, it is difficult to determine whether the effects we estimate can be generalized to other situations. For example, one may question to what extent the weather conditions during the study year (2016) may have influenced the results. Does technical assistance work best during relatively easy farming years in which there are fewer weeds? Only a replication of the estimates in different contexts would allow us to answer this question. We nevertheless believe there are several takeaways from our main findings for the years 2013 and 2016.

First, our main result is quite clear and robust: vineyards participating in the DEPHY network were able to reduce their use of chemical products, especially fungicides. Given that viticulture is heavily reliant on pesticides, the impact of the program is quite large – 8 to 22 percent less pesticides compared to the counterfactual scenario in which no program is implemented.

Second, our results indicate that the reduction in the use of chemicals was accompanied by an increase in the use of biocontrol products. On the one hand this can be seen as a positive impact of the program, since switching from traditional phytosanitary products to biocontrol products is an express intention of the French government. On the other hand, biocontrol substances are known to have negative environmental impacts of their own. While more environmentally friendly than their conventional substitutes, some biocontrol substances still have the potential to degrade the environment, as illustrated by the Asian Ladybird invasions ([Turgeon et al., 2011](#)), and only a portion of these products are officially classified as environmentally innocuous (see the “NODU vert” products).

Third, our results also suggest that the switch from chemicals to biocontrol products resulted in a reduction in yields for a fraction of, but not all, enrolled farms. This result should be seen as encouraging news given that reducing chemical use while maintaining yields was the main objective of the program. It appears that in several cases agronomic choices were relevant since they did not affect yields while allowing for a decrease in pesticide use. These cases can be used as examples of good practices for other farmers to adopt, which was another aim of the program. Additional estimates are, however, needed in order to confirm that these results hold under a variety of weather conditions.

## 7 Conclusion

The purpose of this work was to estimate, at the most disaggregated level, namely the parcel-level, the effects of participation in the DEPHY program. We focused on the emblematic case study of pesticide use in French viticulture. We utilized an approach that addresses the problem of self-selection into the network using a range of quasi-experimental estimators applied to original data on pesticide use and yields. The main results of our analysis suggest that the

program, which provides free technical assistance to peer groups, indeed succeeded in triggering a switch from chemical pesticides to biocontrol products, as well as achieving a decrease in total product use.

More research is needed to strengthen our conclusions regarding the effectiveness of providing free technical assistance to peer groups as a strategy for encouraging improved farming practices. The first direction for further research is to clarify the crucial role played by technicians versus the peer group, as well as their complementarity, in the success of such programs. In particular, further analysis on potential heterogeneity in the treatment effects depending on technician and peer group characteristics is needed. Another direction for further research is the estimation of diffusion effects to evaluate the capacity of the network in disseminating information about new cropping systems and triggering changes in farmer behavior. In addition, and perhaps more urgently, it seems important to enrich the analysis by estimating the effects of the program on the profitability of enrolled parcels. A reduction in yields does not necessarily imply a decrease in profitability. Such a study would take into account the effects of the change in production costs (e.g., lower expenses for chemicals but higher expenses for biocontrol products) as well as the implications for farmers' revenue (possibly lower yields but better quality wine that could be sold at a higher price).

Finally, this paper contributes to the debate about the ability of public policies to play a role in reducing the negative environmental impacts of agricultural activity through the provision of technical assistance to peer groups rather than through conditional compensation schemes. We find that the DEPHY program generates an 8 to 20 percent reduction in total pesticide use for a cost of about 150€/ha/year, which is not greater than the level of the EU AES payment to reduce pesticides. The complementarity or substitutability between technical assistance and conditional payments could be of interest in the continued refinement of more effective agri-environmental programs and ultimately for the pursuit of a transition to sustainable agroecological systems in the near future.

## **Acknowledgments**

This research received financial support from the French National Research Agency (ANR), under grant ANR-16-CE32-0011 and grant ANR-10-EQPX-17 ("Centre d'accès sécurisé aux données" or CASD) as part of the "Investissements d'avenir" program, as well as the grant "Projet jeunes chercheurs SAE2". We thank Nicolas Munier-Jolain, Laurent Delière, Maxime Simonovici, and Clément Fraigneau as well as participants of the INRA-IRSTEA meeting in Montpellier (2018), the INRA-SAE2 Young Researchers Days in Toulouse (2018), the CEEM seminar in Montpellier (2019), the GAEL seminar in Grenoble (2019), the 2019 Univigne conference in Reims (2019), and the 172nd EAAE seminar in Brussel (2019). We thank Kate Farrow and Shannon Harvey for English editing.

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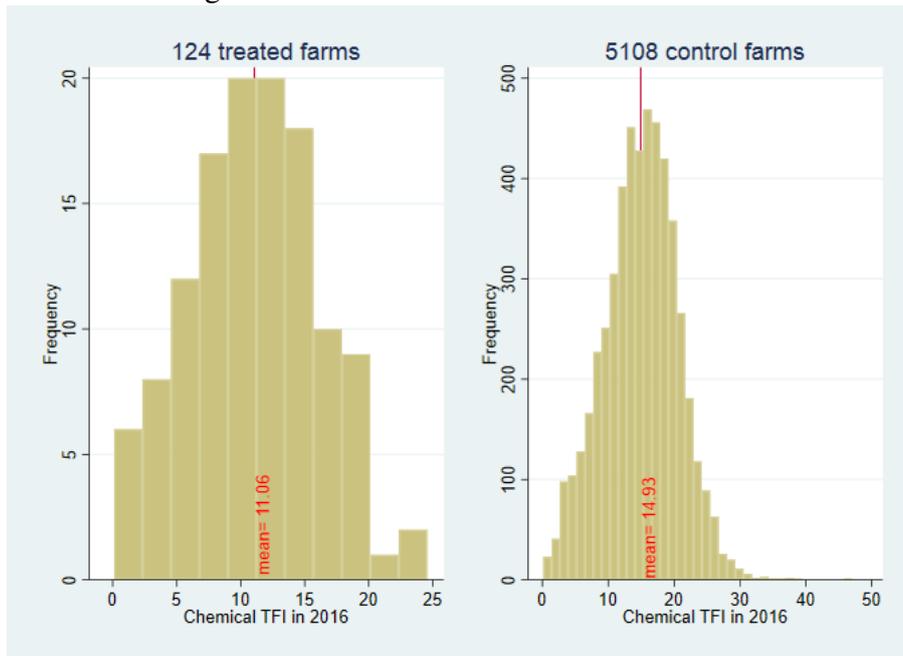
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# **Appendix**

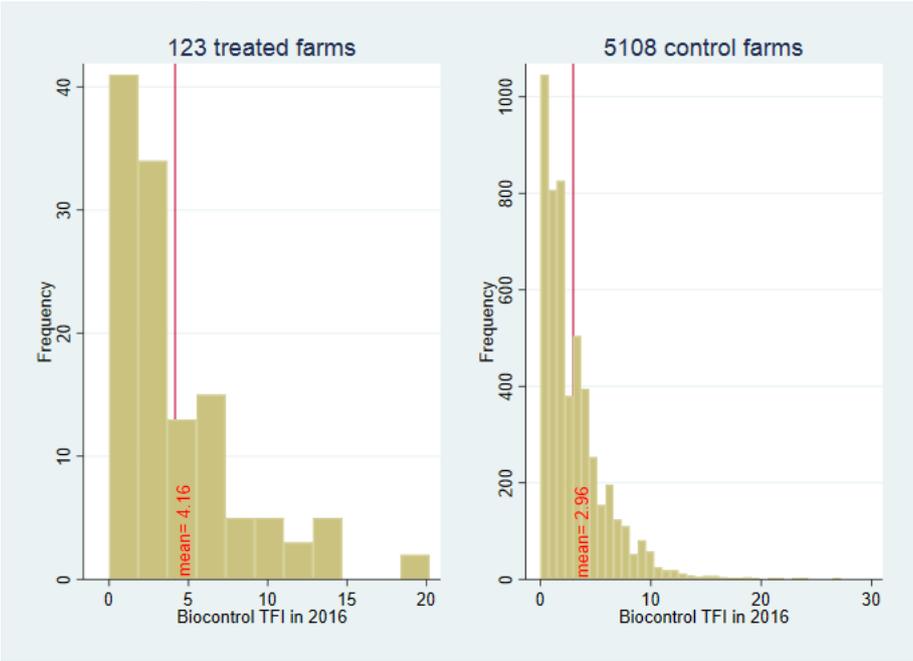
## **Additional figures and tables**

Figure A1: Distribution of the Chemical TFI



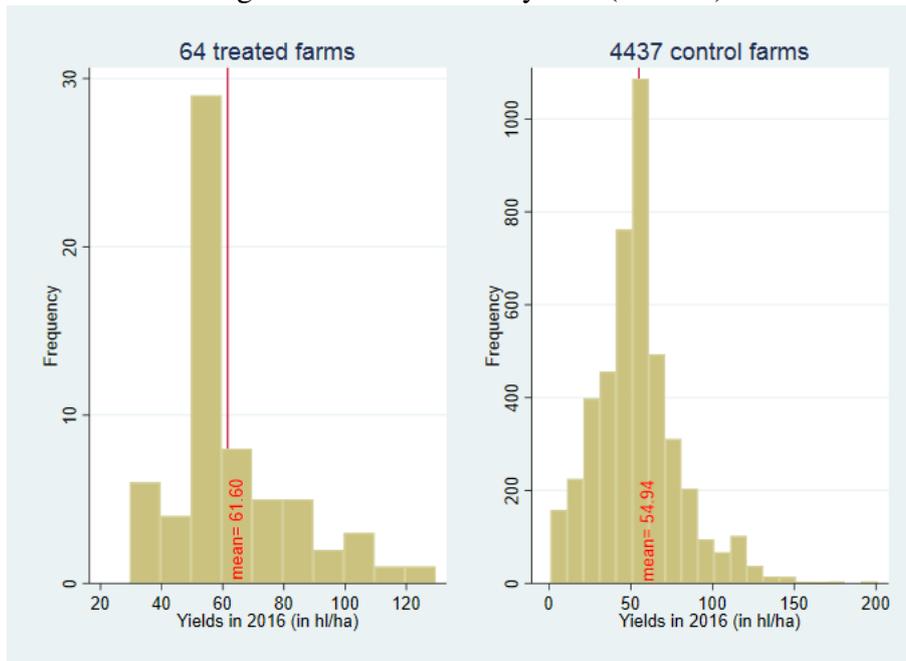
Source: Authors using Agrosyst and MA surveys data

Figure A2: Distribution of the Biocontrol TFI



Source: Authors using Agrosyst and MA surveys data

Figure A3: Distribution yields (in hl/ha)



Source: Authors using Agrosyst and MA surveys data

Table A1: Impacts of the program on second-wave treated units (placebo test)

	DID		DID-matching	
	(3) ATT	(4) Y_1	(1) ATT	(2) Y_1
Chemical (TFI)	-0.74 0.86	12.57	-0.82 1.59	12.93
Biocontrol (TFI)	0.56 0.40	2.32	0.27 0.54	1.79
Yield (hl/ha)	-4.83 3.96	44.67	7.96 8.24	44.17
n_1	36		28	
n_0	3957		1505	

Note: This table provides the estimates of the effects of the DEPHY program on the TFI and yield in 2016 among second-wave treated units using the DID and DID-matching estimators. ATT refers to the average treatment effect on the treated units. Robust standard-errors are in parentheses below the coefficients.  $Y_1$  is the mean value of the outcome of the surveyed plots in the treated group.  $n_1$  refers to the number of treated units in the sample. DID estimates rely on survey data (where the plots considered are not necessarily enrolled in the program). Asterisks \*\*\*, \*\*, and \* denote rejection of the null hypothesis of no impact at the 1%, 5% and 10% significance levels, respectively.

Table A2: Balancing test for characteristics of first and second-wave groups of participants

	First-wave group			Second-wave group			Diff.
	Obs	Mean	Std Dev	Obs	Mean	Std Dev	
On-farm labour	45	9,551	11,173	36	10,273	11,342	-0.05
Climate insurance	45	0.49	0.51	36	0.67	0.48	-0.26
Share of sales in short circuit	45	0.33	1.26	36	0.28	1.16	0.03
Diversification of activities	45	0.16	0.37	36	0.14	0.35	0.03
Calibration of pesticide sprayer	45	0.49	0.51	36	0.53	0.51	-0.05
Sex of head of the farm	45	1.11	0.32	36	1.11	0.32	0.00
Year of birth of head of the farm	45	1,964	9.25	36	1,965	8.43	-0.08
Head of the farm has a bachelor's degree	45	0.69	0.47	36	0.81	0.4	-0.19
Vineyard surface area	45	6,497	9,344	36	8,147	12,668	-0.1
Spouse has agricultural activity	45	0.27	0.45	36	0.44	0.5	-0.26
Spouse has non-agricultural activity	45	0.27	0.45	36	0.31	0.47	-0.06
Wine production	45	0.56	0.24	36	0.62	0.48	-0.11
PDO and PGI production	45	0.81	0.33	36	0.81	0.37	0.00
Utilized agricultural area (UAA)	45	7,532	9,391	36	9,504	14,657	-0.11
Collective management of the farm	45	0.8	0.4	36	0.92	0.28	-0.24
UAA without pesticides	45	0.12	0.26	36	0.07	0.11	0.19
UAA under organic farming	45	0.07	0.22	36	0.11	0.28	-0.12
Surveyed plot is cultivated as organic*	49	0.06	0.24	36	0.11	0.32	-0.12

Note: This table gives the standardized difference in means between the first-wave group and the second-wave group. The variables are taken from the 2010 Agricultural Census. Only the variable with an asterisk (\*) is from the 2010 Farm Practices survey

Table A3: Balancing test for the estimation of the impacts on TFI using DID-matching

	Standardized Differences	
	Before	After
On-farm labor	0.493	0.193
Climate insurance	-0.126	0.114
Share of sales in short circuit	0.615	-0.069
Vineyard surface area	0.458	0.127
Diversification of activities	-0.068	0.000
Calibration of pesticide sprayer	0.611	0.171
Gender of head of the farm	-0.117	0.000
Year of birth of head of the farm	0.128	0.071
Head of the farm got bachelor's degree	0.382	0.063
Spouse has agricultural activity	-0.110	-0.129
Spouse has non-agricultural activity	0.028	0.000
Wine production	-0.104	-0.140
PDO and PGI production	-0.104	-0.140
Utilized agricultural area (UAA)	0.208	0.119
Collective management of the farm	0.570	0.178
UAA without pesticides	-0.118	0.041
UAA under organic farming	0.122	-0.013
Surveyed plot is cultivated as organic	-0.017	0.000

Note: This table gives the standardized difference in means between the treated and the untreated groups, before and after the matching procedure undertaken to estimate the impact of the program on the TFI using DID-matching. The total number of treated is 46.

Table A4: Balancing test for the estimation of the impacts on yields using DID-matching

	Standardized Differences	
	Before	After
On-farm labor	0.532	0.266
Climate insurance	-0.102	0.110
Share of sales in short circuit	0.894	0.066
Vineyard surface area	0.481	0.158
Diversification of activities	-0.285	0.000
Calibration of pesticide sprayer	0.589	0.333
Gender of head of the farm	-0.115	-0.108
Year of birth of head of the farm	0.064	-0.029
Head of the farm has bachelor's degree	0.260	0.039
Spouse has agricultural activity	-0.024	0.042
Spouse has non-agricultural activity	-0.012	0.000
Wine production	-0.104	-0.140
PDO and PGI production	-0.395	-0.295
Utilized agricultural area (UAA)	0.221	0.138
Collective management of the farm	0.776	0.333
UAA without pesticides	-0.077	-0.011
UAA under organic farming	0.190	-0.117
Surveyed plot is cultivated as organic	0.020	0.000

Note: This table gives the standardized difference in means between the treated and the untreated groups, before and after the matching procedure undertaken to estimate the impact of the program on the yields using DID-matching. The total number treated is 34.

Table A5: Balancing test for the estimation of the impacts on TFI using simple matching

	Standardized Differences	
	Before	After
On-farm labor	0.001	0.186
Climate insurance	0.179	0.206
Share of sales in short circuit	0.283	-0.019
Vineyard surface area	0.038	0.094
Diversification of activities	0.212	0.109
Calibration of pesticide sprayer	0.167	0.176
Gender of head of the farm	-0.042	0.136
Year of birth of head of the farm	0.341	0.129
Head of the farm has bachelor's degree	0.541	0.087
Spouse has agricultural activity	0.113	-0.020
Spouse has non-agricultural activity	0.044	0.086
Wine production	-0.225	0.005
PDO and PGI production	-0.027	-0.016
Utilized agricultural area (UAA)	-0.045	0.102
Collective management of the farm	0.355	0.067
UAA without pesticides	0.194	0.091
UAA under organic farming	0.269	0.063
Surveyed plot is cultivated as organic	0.159	0.070

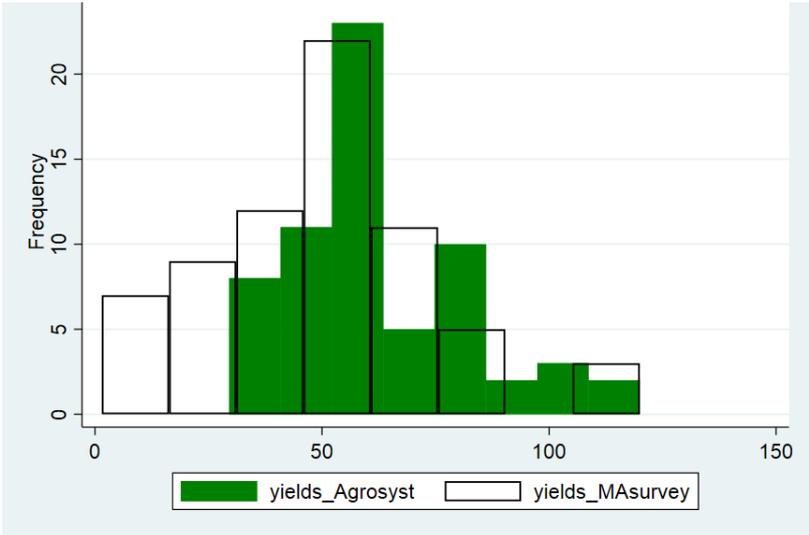
Note: This table gives the standardized difference in means between the treated and the untreated groups, before and after the matching procedure undertaken to estimate the impact of the program on the TFI using simple matching. The total number of treated is 107.

Table A6: Balancing test for the estimation of the impacts on yields using simple matching

	Standardized Differences	
	Before	After
On-farm labor	-0.031	0.033
Climate insurance	0.236	0.213
Share of sales in short circuit	0.125	0.169
Vineyard surface area	0.009	0.031
Diversification of activities	0.332	0.047
Calibration of pesticide sprayer	-0.013	0.137
Sex of head of the farm	0.021	0.173
Year of birth of head of the farm	0.389	0.339
Head of the farm got bachelor's degree	0.400	0.048
Spouse has agricultural activity	0.143	0.000
Spouse has non-agricultural activity	0.038	0.000
Wine production	0.037	-0.008
PDO and PGI production	-0.298	0.010
Utilized agricultural area (UAA)	-0.016	0.070
Collective management of the farm	0.120	-0.047
UAA without pesticides	0.134	0.034
UAA under organic farming	0.218	0.037
Surveyed plot is cultivated as organic	0.255	0.000

Note: This table gives the standardized difference in means between the treated and the untreated groups, before and after the matching procedure undertaken to estimate the impact of the program on the yields using simple matching. The total number of treated is 47.

Figure A4: Distribution of yields in 2016 for DEPHY farms in the two databases



Source: Authors using Agrosyst and MA surveys data

## Details on the construction of the TFI using DEPHY reports

This section describes the methodology for calculating TFI from the information collected in DEPHY reports. We apply the main rules coming from the TFI methodological handbook of the Ministry of Agriculture.

### General principles

The first step to calculate the TFI for each of the treatments declared by the winegrower i.e., for each application of a product during a passage. TFI of a treatment is obtained by dividing the actual applied dose by the reference dose for the product in question, taking into account the proportion of area treated:

$$TFI_{\text{treatment}} = \frac{\text{applied dose}}{\text{reference dose}} * \frac{\text{treated area}}{\text{total area}}.$$

Adjuvants, BC products and product that can be used in organic farming without a marketing authorization are not taken into account in the calculation of TFI. The TFI of a space unit is the sum of the TFI performed on that space unit during a given period, usually the crop year. TFI can be spatially aggregated to obtain, for example, a TFI representative of a farm. Whatever the level of aggregation, the principle is the same: the TFI is a weighted average of the TFI of space unit.

### Reference doses

Reference doses are established on the basis of information on authorized products and uses, for each crop year. There are two types of reference doses:

- Reference doses for the target: defined for each product, crop, pest or function to be treated (herbicide, fungicide etc), and correspond to the maximum authorized dose for each product and use.
- Reference doses for the crop : defined for each product and crop, and correspond to the minimum of the reference doses defined for the target for the product and crop in question.

Here we consider this latter reference dose because DEPHY records of pesticide application do not provide information on the target. Conversions are made when the applied dose is not expressed in the same unit as the reference dose.

### Adjustments

The adjustments concern three types of situations: - TFI of a treatment cannot be calculated because one or more necessary information is missing (e.g. the reference dose) or the units are incompatible. - TFI of a treatment is considered abnormal i.e., it is not included between 0.1 and 2. In the first case, the adjustments consist in substituting the ratio of doses by 1 if a dose is missing or units incompatible and substituting the proportion of surface treated by 1 if missing. In the case of an abnormal TFI, its value is substituted by 1.

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