Internship report

Impact of the DEPHY network on pesticide use: Evidence from French vineyards

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Do not circulate. Results using the 2016 "Pratiques Culturales" survey are not to be displayed before the first governmental publication using these data (probably in 2019).

1. Introduction

After the Second World War, food insecurity prompted many countries to increase their agricultural production and productivity. Pesticides were part of the growth package. Regrettably, a growing number of studies report negative externalities from such use on the environment and human health. Pesticides spread and contaminate air, soil and water, with adverse effects on quality of ground and surface waters, soil fertility, biodiversity and human health, particularly for users (Wilson and Tisdell, 2001). As illustration, in France, when pesticides are sprayed on foliage, it is estimated that 10 to 70% is lost to the soil and 30 to 50% to the air (Aubertot et al., 2007). Many countries in Europe have introduced pesticide use reduction policies but there has been no downward trend (EUROSTAT, 2018). Among national initiatives, the French National Action Plan "Ecophyto" has been set up in 2008, with the objective of halving pesticide use by 2018. At the moment, transition towards a 50% reduced pesticide use is not achieved and the end of the plan was postponed to 2025.

An important component of the Ecophyto plan is the DEPHY network, created in 2010 to demonstrate the feasibility of this objective. It is constituted of local groups of a dozen farmers supported by an engineer, who test cropping systems consuming less pesticides. The individual and collective support combined with the sharing of knowledge and experience must contribute to deploy efficient agricultural systems and practices. Furthermore, the government plans to expand the DEPHY network to 30000 farmers to enhance its effectiveness. To justify this expansion and attract new participants, a first step is to ensure that participating farms are actually effective in reducing pesticide use.

One of the main challenge being to do so while maintaining high crop productivity.

A recent empirical study (Lechenet et al., 2017) assesses the possibility to decrease pesticide use in the French arable sector. The authors have analyzed data collected on farms involved in the DEPHY network. They do not detect any conflict between reduction in pesticide use and productivity in 77% of DEPHY farms. By comparing each of these farms to a reference farm sharing the same constraints and opportunities but with lower pesticide consumption, they suggested that pesticide use could be reduced by 42% in 59% of DEPHY farms without productivity and profitability loss. However, they did not evaluate the effectiveness of the program to encourage farmers to achieve such reductions. Indeed, the absence of non-DEPHY farms in the study sample is a major pitfall, due to the voluntary nature of the program.

In this paper, we examine the causal effect of participation in the DEPHY network on pesticides use in wine production, using microeconometric methods of impact evaluation. We propose an approach that explicitly takes into account the self-selection of participants by comparing data from the DEPHY network to detailed national surveys at the farm level. We try the answer the following questions: is it possible to halve pesticide use? Is the support of a technical engineer an effective solution to do so? Our parameter of interest is the additionality of this program: how much pesticide reduction has been achieved thanks to the program. We use various identification strategies to estimate the impact of the program including matching and Difference In Difference (DID) matching procedures. We find that DEPHY farms have achieved reductions in pesticide use that ranges from 16 to 31%, thanks to the program.

The rest of the paper is organized as follows. The next section 2 analyzes the possibility of reducing pesticide use in Europe. Section 3 describes the data, measures and estimators we use. The implementation and results of the matching procedure are presented in Section 4, as well as DID matching estimates. Finally, Section 5 briefly concludes, by underlining the policy implications of our results, and gives directions for further research.

2. Exploring the possibility of reducing pesticide use

2.1. Reasons and limits of pesticide use

Pesticides affect yields through the management of agricultural pests (pathogens, animal pests and weeds), they preserve the crop's potential. For example, herbicides are used to control weeds that compete with crops for soil nutrients, water, light, and space. Hence, pesticides are not a direct production factor. Applying fungicides on a crop without any risk of disease does not increase yields but input costs. To know if a pesticide application is efficient, one must know the yield loss that the crop would have suffered in its absence. Determinants of pest prevalence are now well documented. Climatic conditions are the main driver since it affects water and light availability. Warm and humid weather tends to favour many pests (Rosenzweig et al., 2001). The type of crop variety and the abundance of natural enemies of pests (Östman et al., 2003; Petit Michaut et al., 2015) also play an important role. Lately, the increasing virulence of many species of pests due to pesticide-resistance among pest populations and pesticide side-effects on natural enemies questions the benefits of pesticides. The extensive and continuous use of pesticides could threaten agricultural production and sustainability (Wilson and Tisdell, 2001), as suggested by yield stagnation or decline occurring in some areas (Ray et al., 2012). At the same time, a growing number of studies show that use of pesticides is generally not optimized (Gaba et al., 2016; Mailly et al., 2017; Nave et al., 2013), that alternatives exist (Lamichhane et al., 2015; Andert et al., 2016; Petit et al., 2015; Reau et al., 2010) and suggest that substantial reductions in pesticide use can be achieved without impact on productivity or profitability (Jacquet et al., 2011; Lechenet et al., 2017).

2.2. Strategies to reduce reliance on pesticide use

Logical farming, Integrated Pest Management (IPM) and organic farming are alternative solutions for decreasing reliance on pesticides. In particular, IPM takes advantage of all appropriate pest management options (including but not limited to pesticide use), and then appears more profitable than its organic counterpart (excluding the use of pesticides) and enables greater reductions in pesticide use than logical farming (which optimizes pesticide use on the basis of observations and the use of decision-making tools). One of the possible options is for example the diversification of crop rotations, which can interrupt disease cycles or reduce the abundance of dominant weed species (Andert et al., 2016). A large number of the studies point out opportunities for significant reductions in use of pesticides without impacting productivity or profitability[1]. For example, Jacquet *et al.*

[1] The literature dealing with pesticide use reduction is generally based on data from observations on a few farms (Nave et al., 2013; Petit et al., 2015) or from agronomic experiments (Hossard et al., 2014; Petit et al., 2015; Reau et al., 2010; Jacquet et al., 2011), and analyze the efficiency of low-pesticide innovative cropping systems on a range of sustainability indicators.

(Jacquet et al., 2011) have constructed cropping system[2] prototypes based on results of agronomic trials and expert knowledge, and have simulated the economic effects of different levels of pesticide reduction in France. They find that decreasing use of pesticides up to 30% at the national level could be possible without reducing farmers' income. Their results also indicate that integrated production systems are the most efficient to balance pesticide reduction and farmers' profit. But while IPM is more and more popular in orchards and greenhouse cropping systems, it remains marginal in arable and field crops. In this context, understanding why some farmers adopt alternatives to pesticides while others do not is of interest.

2.3. Factors limiting the adoption of alternatives to pesticides

The increase in volumes of pesticides sold in 16 European Union (EU) countries[3] between 2011 and 2016 (EUROSTAT, 2018) reflects insufficient adoption of innovative crop systems by farmers. Although the efficiency of IPM relies on the diversity and the simultaneity of complementary practices, partial or step-wise adoption is often observed among farmers (Bailey et al., 2009). Indeed, a wide range of IPM-based methods are available but farmers have little guidance for implementing and combining it optimally according to agro-climatic and crop-specific growing conditions. Research often provides

[2] A cropping system is defined by the crops, crop sequences and the management techniques implemented on a field.

[3] According to the article on consumption of pesticides in the EU by Eurostat(EUROSTAT, 2018), "16 EU Member States provided non-confidential data for all major groups [of pesticides] in 2011 and 2016. [...] The total volume of pesticide active substances sold in these 16 EU Member States increased only slightly, by 1.6%. It is important to note that many of the more hazardous substances have had their authorization withdrawn, and been removed from the market, following their evaluation under Regulation (EC) No 1107/2009 concerning the placing of plant protection products on the market."

evidence of the efficiency of single strategies which have yet to be tailored as part of an whole IPM system. Furthermore, farmers often perceive the adoption of new practices as risky, due to the novelty and the need to learn how to manage new systems (Musser et al., 1981). There is also a lack of field evidence on the impact of the adoption of IPM-based practices on management and labour costs, especially in the European context. IPM is generally more time-consuming and requires more information and knowledge than conventional methods (Beckmann and Wesseler, 2003; Waterfield and Zilberman, 2012). Consequently, an immediate switch can not be expected, which constitutes a rational for public intervention. But this makes it difficult to forecast the efficiency of programs promoting IPM and to set pesticide reduction targets.

2.4. Policies encouraging alternatives to pesticides in Europe

Since the mid 1980's, many European countries have adopted pesticide reduction policies. For example, Sweden, the Netherlands and Denmark launched the first national initiatives for pesticide reduction in the EU, build upon research/training/advice programs, regulatory measures or taxes on pesticides. The three countries reached their target to halve pesticide use in 10 years without adversely affecting yields (Neumeister, 2007). However, they launched programs to reduce the volume of pesticides used when new low-rate herbicides were introduced. In fact, the quantitative changes were driven by the efficacy of lower doses of herbicides, not due to the pesticides reduction policies (Gianessi et al., 2009). Moreover, in the early 2000's, pesticide use started to increase again in Denmark and The Netherlands, and both countries moved from a volume reduction target to an impact reduction target. Thus, over the years, many approaches have been developed to encourage pesticide use reduction.

Some countries have decided to rely on incentive-based instruments (taxes and subsidies). Taxes on pesticide use have been introduced in Sweden (1984), Denmark (1996), Norway (1998) and France (2000), with contrasting results (Lefebvre et al., 2015). Pesticide taxes alone appear to be ineffective due to the low price elasticity of pesticide use and the high tax rates needed to achieve a reduction (Jacquet et al., 2011). In parallel, Agro-Environmental Schemes (AES) have been introduced under the Common Agricultural Policy to foster the adoption of farming practices that aim to benefit the environment or biodiversity. Some options target pesticide use reduction, in particular through the adoption of IPM practices. Voluntary farmers are compensated for the costs associated to the learning phase of adoption, the riskiness of the new practice and the collection of experiences and information that will benefit other farmers interested in adoption (Lefebvre et al., 2015). However, the effectiveness of AES can be moderated by windfall effects, especially for options with modest requirements (Chabé-Ferret and Subervie, 2013). Indeed, participation in an AES is voluntary, requirements and per-hectare payments are generally uniform, and hence, these schemes are likely to attract mostly farmers with the lowest compliance costs and to pay for practices that would have been adopted in its absence. A recent empirical study (Kuhfuss and Subervie, 2018) estimates that AES targeting the use of herbicides in French vineyards decrease herbicide use intensity by 40-50%. The authors demonstrate that least stringent but most adopted AES options (e.g. zero herbicide between the vine rows) are effective in reducing herbicides when weed pressure is high, whereas more stringent AES options (e.g. organic farming) reduce herbicide use even when less weed pressure is experienced. In this context, another drawback of AES is that it encourages the adoption of single and crop-specific practices instead of promoting IPM as a whole system (Lefebvre et al., 2015).

In recent years, the EU legislation has also been modified and various regulations has been released. It includes, for example, restrictions on the use of certain pesticides (maximum levels of concentration for pesticide residues in food (EU, 2005), authorization withdraws (EU, 2009c)) and requirements on technologies used by farmers (spraying materials (EU, 2009a)). In particular, the European Directive 2009/128/EC on Sustainable Use of Pesticides (EU, 2009b) mandates all professional users to adopt the principles of IPM and calls the Member States to ensure the adoption of IPM through crop-specific guidelines which remains voluntary.

To this end, agricultural extension services has a central role: the Member States have to provide farmers with the necessary information, tools and advisory services to adopt IPM. Educational programs, training activities and advisory services offered to farmers have demonstrated their usefulness (Kudsk and Jensen, 2014; Bailey et al., 2009) and are essential components of the National Action Plans set up by the EU countries. Collective approaches to implementation appears to be the most efficient (Reau et al., 2010; Kudsk and Jensen, 2014). It allows to spot common problems, to influence farmers' perceptions of risks associated with the novelty of alternative practices and their beliefs in their own abilities to carry it out (self-efficacy), and to benefit from collective experiences (Lamichhane et al., 2015). It makes the DEPHY network of particular interest.

2.5. A collective program to tackle the excessive use of pesticides

An important program of the French Ecophyto plan is the DEPHY network. This network has two components: the DEPHY-FERME program, a demonstration and reference production network that gathers 3000 farmers engaged in a voluntary approach to reduce pesticides, and the DEPHY-EXPE program, an experimental network gathering projects testing low-pesticide cropping systems (with the objective to reduce pesticide use by at least 50%). After a test phase which started in March 2010, the DEPHY-FERME program has gathered about 3000 farmers since 2011. A network engineer is in charge of the individual and collective support of a group of a dozen farmers in the same crop-sector and often sharing similar problems. She builds with each farmer in her group an individual project to reduce pesticide use over 5 years, based on an initial diagnosis of the farm. She then supports the implementation of this project and monitors its progress through campaign reviews and the annual recording of practices. The farmers' individual projects are based on a collective project driven by the group through meetings, demonstration days etc. The aim of the DEPHY-FERME program is to acquire references that describe the functioning and evolution of the performance of certain low-pesticide and economically efficient cropping systems. The network shares its experience and results through local communication and demonstration actions in order to disseminate successful experiences. The government plans to expand the network to 30000 farmers in order to enhance its effectiveness, but a first step is to ensure that participating farms actually reduced their pesticide use.

3. Empirical strategy

To estimate the impact of participation in the DEPHY network on the level of pesticide used by DEPHY winegrowers, we use a matching approach which consists in pairing one farm of the network to a control farm having similar characteristics but that did not benefited from the DEPHY program. The relevant unit of analysis is the cropping system, the level from which the pest control strategies are developed. We use data for the crop years 2010 and 2016[4]. Year 2010 is before the introduction of program, this allows to build a control group based on characteristics not affected by this latter. Then, we estimate the impact of the program in 2016. In this study, we focus on the wine growing sector because it is the only crop sector for which we have pre and post-program data for the control group. Note that the wine growing sector is of particular interest since this is the crop sector that uses the highest quantity of pesticides. This section presents the variables and data sources we use, and describe the parameter we aim to estimate and our identification strategy.

3.1. Measure of pesticide use

We measure pesticide use by the Treatment Frequency Index (TFI), developed by Denmark to monitor intensity of use and not simply volumes of pesticides. It refers to the number of pesticide applications per hectare, based on reference doses of commercial products:

$$TFI = \sum \frac{applied\_dose}{reference\_dose} * \frac{treated\_area}{total\_area}.$$

[4] A crop year generally begins in September of year n-1 and ends in September of year n. Year n is the year of harvest, the year used to name a crop year.

The reference dose corresponds to the efficient dose of a product for a specific crop. For example, a TFI of 1 is equivalent to one full dosage treatment applied to a given area. The annual TFI of agricultural land is the sum of the TFI calculated for each treatment carried out on those land during a crop season. In France, this indicator is used in the context of public policies follow up such as pesticides-related AESs and the Ecophyto plan. Thus, the DEPHY network collects detailed data on pesticide application by farmers since joining the network (either in 2011, 2012)[5]. We are able to derive annual TFI for 185 cropping systems over the period 2011 to 2016. A TFI at the cropping system-level synthesizes the TFI of several parcels cultivated in the same way. Figure 1 shows the geographic distribution of DEPHY vineyards in which the main wine-growing regions are represented. Furthermore,

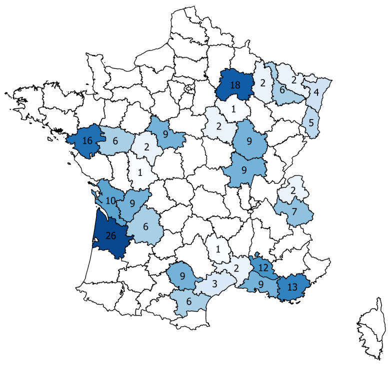

Figure 1: Geographic distribution of the DEPHY vineyards. Source: Authors using Agrosyst data.

records of pesticide treatments applied on a large sample of French vineyard parcels is also available for the crop years 2010, 2013 and 2016 via the "Pratiques Culturales" (PK) surveys in wine growing. Conducted every three years by the Department of Statistics of the Ministry of Agriculture, these surveys aim to collect representative panel data on the grapevine management techniques and to estimate national and regional TFI. This allows

[5]The data on DEPHY vineyards was extracted from the Agrosyst database.

us to calculate annual TFI for 4390 parcels which responded to at least two of the three surveys. Therefore, the TFI of DEPHY winegrowers can be compared to the TFI of PK surveys respondents that do not participate to the program. For this, we consider TFI at the cropping system-level. We assume that the variability within the cropping system is quite low in wine growing so that the PK surveys parcels are representative of the cropping system which it belongs. We did not use the TFI calculated by the DEPHY network and the Department of Statistics because they did not follow the same rules, thus any difference between the two groups could be attributed to the way the indexes were build. The general principles we use to construct the TFI are described in Appendix A [6]. Nevertheless, we were able exploit some sophisticated measures of the TFI extracted from the PK surveys database (Agreste) such as the TFI for biological products (BC) products and the TFI including or excluding BC products, both calculated by the Department of Statistics of the Ministry of Agriculture. BC products do not refer to products authorized for organic farming, but products that use natural action and/or interaction mechanisms. Then, they are considered as an alternative to conventional pesticides and are generally excluded from the calculation of the TFI. Table 1 reports the average TFI of both groups per year. The average TFI of DEPHY vineyards show a clear downward trend, whereas the average TFI of non-DEPHY vineyards has increased. The year 2012 was characterized by marked rainfalls that generally resulted in an increase in wood diseases in French vineyards. This may explain the drastic increase in pesticide use this year among DEPHY vineyards. We can not exploit every annual TFI for the DEPHY group because comparisons are only

[6] We apply the main rules coming from the TFI methodological handbook of the Ministry of Agriculture (agr, 2018)

Table 1: Average TFI

Year	mean TFI (non-DEPHY)	mean TFI (DEPHY)
2010	14.34 (3091)[a]	13.21 (40)[b]
2011		10.72 (21)
2012		15.23 (59)
2013		11.16 (80)
2014		9.46 (142)
2015		8.03 (127)
2016	15.64 (3091)[a]	10.11 (140)

Source: Authors using Agrosyst and Agreste data.
Sample size in parentheses.
[a] Non-DEPHY vineyards were lost due to the absence of pesticide-related data in 2010.
[b] The TFI was calculated using the Agreste data on 40 DEPHY winegrowers that responded to the PK survey in 2010.

possible for years 2013 and 2016. However, this latter was of reasonable size (140 cropping systems[7]) only in 2016 so we focus on this year. Pesticide use differ between the two groups since the beginning of the program but these differences may not be fully attributed to this latter. Indeed, to join the DEPHY network, a farmer must apply to an organization in charge of formation of DEPHY groups and commit for 3 years to a collective project. The farmers who build a case and are selected in the program are probably the most motivated farmers, already engaged in or planning to reduce their pesticide use. Thus, these farmers would have achieved substantial reductions even in this absence of the program. That is the reason why a simple comparison between the TFI of participants and non-participants is not sufficient to evaluate whether the DEPHY program actually encourages farmers to reduce their pesticide use. We address the issue of self-selection by a matching approach in order to estimate the additional effects of the program.

[7]45 DEPHY vineyards were lost due to the absence of pesticide-related data in 2016 or covariate missing values

3.2. Determinants of pesticide use and participation decision

To ensure a relevant comparison, we have to identify vineyards that were similar in terms of pesticide use before the program. However, we do not have the pre-program TFI of the DEPHY vineyards. To address this issue, a control group is selected among the non-DEPHY vineyards on the basis of observable characteristics shared with the DEPHY group. Only factors explaining use of pesticides and participation decision should be included. In addition, it is crucial that these factors are unaffected by the program. Thus, variables should either be fixed over time or measured before the entry into the network. To ensure this, we use data coming from various sources.

First, the French Agricultural Census conducted in 2010, i.e. before the program, collects farm-level data on the structural characteristics of farms (land use, livestock and labour force) and management practices. Thus, it provides a range of agronomic, social and economic variables likely to influence use of pesticides and decision to join in the DEPHY network including details on: the manager (age, sex, education/training, spouse's main activity), on the farm (ownership, group holding, on-farm labour, cultivated areas, insurances, diversification activities), on the production (size, quality labels, local distribution network), and on farming practices (pesticides spraying, area without pesticides, organic farming).

Second, specific data on cropping systems comes from the DEPHY network for the participants and from the 2010 PK survey for the non-participants. In fact, when a farmer joins the DEPHY network, average data related to the last few years is collected as part of the initial diagnosis of the farm. For example, a farmer joining the network in 2012 will describe its average practices over the period 2009-2011. Thus, we have information on pest control management strategy before participation to the program for both groups, including use of grassing (IPM), organic farming and presence of the Carignan grape variety which is especially sensitive to specific diseases. These variables are used as covariates in all matching procedures and are extensively described in Appendix B.

3.3. Estimators

Our objective is to estimate the causal effect of participation in the DEPHY program on the level of pesticides used by participants, namely the Average Treatment effect on the Treated (ATT)[8]. The ATT is defined as the mean difference between the TFI of vineyards involved in the DEPHY network and what these levels would have been in the absence of the program (the counterfactual situation):

$$ATT = E[TFI^1 - TFI^0|D = 1] = \underbrace{E(TFI^1|D = 1)}_{observed} - \underbrace{E(TFI^0|D = 1)}_{notobservable}$$

where TFI^1 is the TFI in the presence of the DEPHY program, TFI^0 is the TFI in the absence of the program and D is the treatment variable that is equal to 1 for the DEPHY winegrowers (the treated) and 0 otherwise. Clearly, the counterfactual situation is not observable and we do not know the difference between the winegrower's pesticide use with and without the program. If we compare the TFI of DEPHY vineyards to their pre-

[8] Another parameter of interest is the average treatment effect (ATE) which represents the average impact of treatment if every winegrower in the population participates in the DEPHY program. However, both counterfactual outcomes have to be constructed and the size of our sample of DEPHY vineyards is too small to do so.

program level, our estimator of the ATT may suffer from a time trend bias, due to changes in climatic conditions over time, for example. Comparing the TFI of DEPHY vineyards to those of the non-DEPHY vineyards (the untreated) could introduce a selection bias, due to covariates that simultaneously determine the TFI and the decision to join the network. As explained previously, we can expect that the two groups had already different TFI before the program or that it would have evolved differently in the absence of the program.

To address this problem of self-selection, we pair DEPHY and control winegrowers (the matched) who are similar in terms of observable factors X likely to affect both participation and pesticide-related decisions. Doing so ensures that matches have a similar probability to join the network and are likely to have similar pre-program TFI which would have evolved alike without intervention. Then, the ATT can be written as:

$$ATT^X = E(TFI^1|D = 1, X) - E(TFI^0|D = 0, X)$$

Our identification strategy relies on three assumptions. First, we assume that selection is only based on observable factors, meaning that the TFI is mean independent of program participation conditional on observable covariates. It is the conditional independence assumption. The second assumption, called the Stable Unit Treatment Value Assumption (SUTVA) (Rubin, 1978), imposes that the effect of the DEPHY program for each winegrowers is independent of participation in the program of other winegrowers. In other words, the TFI of non-DEPHY winegrowers have not been altered by the program. If some DEPHY winegrowers have shared their experience and results with non-DEPHY winegrowers, which is plausible given the objectives of the program, this would lead to an underestimation of the ATT. However, the PK surveys allow to identify winegrowers who visited or attended demonstrations in DEPHY vineyards, then we exclude them from the sample. Third, we assume that there is overlap between both groups, which means that there is no perfect predictability of participation given the covariates.

The general form of the cross sectional matching estimator is then (Abadie et al., 2004):

$$\widehat{ATT^X_{csm}} = \frac{1}{n_1} \sum_{i \in I_1 \cap Sp} \left(TFI^1_i - \sum_{j \in I_0} \lambda_{ij} TFI^0_j \right)$$

where I_1 denotes the DEPHY vineyards, I_0 denotes the control vineyards, n_1 is the number of DEPHY vineyards in I_1, S_P denotes the common support and λ_{ij} the are weights assigned to potential matches given their covariates values. Similarity between winegrowers is based on a weighted function of the covariates X for each observation or on estimated treatment probabilities P(D=1|X), known as propensity scores (Rosenbaum and Rubin, 1985). The propensity score is the probability for a winegrower to participate in the DEPHY program given his covariate values. As the number of covariates increases, it is more difficult to find comparable vineyards (the so-called curse of dimensionality), then propensity score matching perform better than covariate matching. Thus, we can match each participant to one or more non-participants by looking at the smallest distances between two vectors X or between two propensity scores P(X). We perform full Mahalanobis covariate and propensity score matching both with one and two nearest neighbors[9] and

[9]In the case of propensity score matching, the maximum distance for which two observations are potential neighbors can be specified by the caliper width. In our case, the choice of caliper width did not impact the estimates so we do not use any caliper.

with robust Abadie–Imbens standard errors (Abadie et al., 2004; Abadie and Imbens, 2006). We also allow control vineyards to be used as a match more than once.

Furthermore, there are two types of selection bias: selection on observable characteristics (education, age, farm size...) and selection on unobserved characteristics (management ability, environmental awareness). One of the identification conditions required for matching is that selection is only based on observable factors (CIA). However, we can not rule out the possibility that there is unobserved heterogeneity between DEPHY and control vineyards. We also propose to implement a DID matching procedure using 40 DEPHY winegrowers that responded to the PK survey run in 2010. The DID matching tackles the issue of selection bias in two steps: first, it deals with selection on observable characteristics by comparing DEPHY vineyards to control vineyards having the same observed characteristics before the program, and second, it addresses selection on constant[10] unobserved characteristics by subtracting the difference in pesticide use before the program between DEPHY and control vineyards. Thus, we compare changes in various TFI over the period 2010-2016 between DEPHY and control groups instead of comparing TFI in 2016 between both groups. The general form of the DID matching estimator is then (Abadie et al., 2004):

$$\widehat{ATT^{X}_{ddm}} = \frac{1}{n_1} \sum_{i \in I_1 \cap Sp} \left(\delta TFI^1_i - \sum_{j \in I_0} \lambda_{ij} \delta TFI^0_j \right)$$

where δTFI is the change in TFI over the period 2010-2016, I_1 denotes the DEPHY

[10] The DID matching procedure does not eliminate selection bias due to unobserved factors that vary over time.

vineyards, I_0 denotes the control vineyards, n_1 is the number of DEPHY vineyards in I_1, S_P denotes the common support and λ_{ij} the are weights assigned to potential matches given their covariates values. The results of the cross sectional matching and DID matching procedures are presented in the next section.

4. Additional effects of the DEPHY network

We estimate the ATT by matching on a sample of 4530 vineyards including 140 DEPHY vineyards. We present and discuss the estimation's results in this section. We assess matching quality using balancing tests that indicate whether the control vineyards are close enough to the DEPHY vineyards with which they are associated. In addition, Difference in difference (DID) and DID matching estimations are implemented on a sub-sample 3131 winegrowers that responded to the PK surveys in 2010 and 2016, including 41 DEPHY winegrowers.

4.1. Implementation of the matching procedure

The first step of our estimation procedure is to estimate a logit participation model which includes all of the covariates previously mentioned. The result of the logit regression is given in Appendix C. It suggests that participation is not random, there is selection on observable characteristics: DEPHY vinegrowers tends to be younger and more educated, they are more inclined to use grassing and to grow a variety prone to diseases. They also have a stronger preference for organic farming, but quality labels (AOP, IGP) tends to decrease participation in the network. The results are generally consistent with previous empirical works dealing with pesticide use (Kuhfuss and Subervie, 2018).

Given the estimates from the logit model, we then compute the propensity scores. Figure 2 shows the density distributions of propensity scores by groups. The support problem can be spotted by simple visual analysis of the distributions. The estimated probability of being in the DEPHY network ranges from 0.002 to 0.31 for the DEPHY vineyards and from 0.00004 to 0.52 for their non-DEPHY counterparts[11]. The propensity score is balanced across the DEPHY and non-DEPHY groups so the matching procedure is likely to perform well.

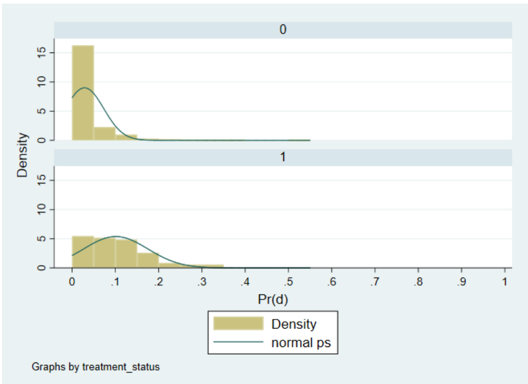

Figure 2: Density of propensity scores by group.

We assess matching quality by checking whether the different procedures were able to balance the distribution of the covariates. For this, we compare the normalized differences in covariate means[12] between the DEPHY group and the control group (the matched) before and after the matching procedure (Rosenbaum and Rubin, 1985), using a rule of

[11]It has to be kept in mind that the propensity score estimation aims to balance all covariates across DEPHY and non-DEPHY vineyards, not to predict selection into the network as good as possible (Caliendo and Kopeinig, 2005).

[12]The normalized difference is the difference in means between the two groups considered divided by the square root of the sum of variances for both groups.

thumb of 0.25 standard deviations (Imbens and Wooldridge, 2009). The balancing tests of all matching estimators are in Appendix D. Table 2 gives the results of balancing test for our preferred specification, the 2-nearest neighbors estimator based on propensity score.

Almost all the normalized differences after matching are below the normalized differences before matching. Thus, the matching significantly removed the differences in covariates between the DEPHY group and the control group. Moreover, all the normalized differences after matching are below 0.25 standard deviations, confirming the success of the estimation.

4.2. Results from the cross sectional matching procedure

Table 3 reports the matching estimators and the ATT estimated by an Ordinary Least Squares regression (OLS) of the TFI on the participation variable and the pre-program covariates, with robust standard errors.

Table 3: Treatment effects estimation using matching procedures and OLS regression

Estimation methods	PS (logit)	PS (logit)	NN (mahalanobis)	NN (mahalanobis)	OLS
ATT	-4,22	-3,26	-4,30	-4,55	-4,54
Standard errors	0,58	0,63	0,67	0,67	0,58
Nb. of treated	140	140	140	140	140
Nb. of controls	4390	4390	4390	4390	4390
Min nb. of neighbors	2	1	2	1	-
Max nb. of neighbors	4	3	8	3	-

Notes: In column 1 (resp. 2), “PS” refers to the nearest neighbour estimator using two (resp. one) matched observations and the propensity score P(X) (estimated using a logit participation model). In column 3 (resp. 4), “NN” refers to the nearest neighbour estimator using two (resp. one) matched observations and the vector X (using Mahalanobis distances). In column 5, “OLS” refers to the Ordinary Least Squares estimator.

The estimates are generally stable and precise. All are different from zero at the 1% level of significance. Figure 3 gives a representation of confidence intervals of the

Table 2: Balancing test before and after the 2-nearest neighbors matching procedure based on propensity score.

Variable	Normalized differences Raw (2)	Matched (1)
On-farm labour	0,18	0,08
Insurance	0,02	-0,03
Solidarite	0,11	0,05
Local distribution network	0,37	-0,12
% of production in local distribution network	0,06	-0,05
Diversification	0,25	0,03
Organic conversion	0,22	-0,04
Sprayer calibration	0,19	-0,01
Sex	-0,01	0,02
Date of birth	0,36	0,00
Baccalaureat	0,65	0,00
Vineyard surface area	0,16	0,14
Spouse's activity: Agricultural	0,09	0,07
Spouse's activity: Non-agricultural	0,14	-0,02
% of vineyard surface	0,25	-0,06
Production	-0,13	0,15
AOP/IGP production	-0,11	-0,09
UAA	0,00	0,15
Farmer association	0,43	0,04
Ownership	-0,34	-0,01
UAA without pesticide	0,08	-0,05
External treatments	-0,27	0,03
% of organic farming surface	0,26	-0,03
Organic farming	0,29	0,02
Grassing	1,02	-0,01
Carignan	0,11	0,02

Note: Column 1 reports the normalized mean differences between the treated group and the untreated group. Column 2 reports the normalized mean differences between the treated and the winegrowers from the untreated group who were selected in the matching procedure using a minimum of two 2 nearest neighbors and based on propensity score. The normalized difference is the difference in means between the two groups considered divided by the square root of the sum of variances for both groups. Nb. of observations: 4530.

matching estimators. Our preferred estimator, the 2 nearest neighbors estimator based on propensity scores, indicates a negative difference in TFI of 4.22 points between DEPHY and control groups. The average TFI is 10.14 in the DEPHY group so it would have been 14.36 (+4.22) in the absence of the program. It means that the program reduces the average TFI of participants by 29%. For the other matching specifications, TFI reductions range from 24% to 31%. This suggests a strong effect. Unlike matching, OLS regression does not allow for heterogeneous impact of the program[13] but yields more precise estimates since all the observations of the sample are used. Our linear estimator indicates that the average TFI of participants is 31% below what it would have been without the program, which is consistent with the matching estimates.

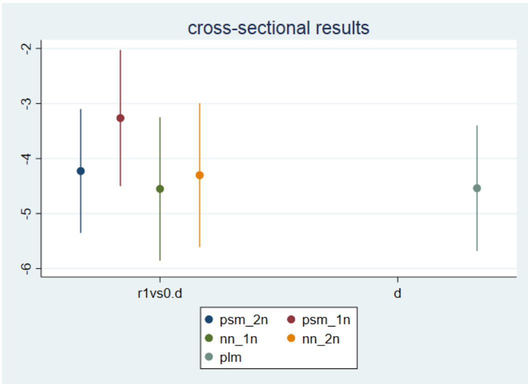

Figure 3: Matching (on the left) and OLS (on the right) estimators and their confidence intervals.

4.3. Results from DID matching and DID procedures

We test the sensitivity of our results by implementing DID matching and DID procedures on a subsample of 3131 winegrowers that responded to the PK surveys in 2010

[13]If the program effect varies with the covariates, applying OLS without interactive term estimates a weighted average of heterogeneous effects, such as ATT, but the weights are not the same.

and 2016 including 41 DEPHY winegrowers, which means that we have TFI values before and after the introduction of the DEPHY program. To check whether our matching estimators are robust against the 'hidden bias' due to unobserved factors, we propose a DID matching approach. Interestingly, 40 DEPHY winegrowers have participated in the PK surveys run in 2010 and 2016, providing their pre-program TFI. It constitutes a large enough sample to implement a DID matching procedure and ensure accurate results. It also allows us to exploit the sophisticated measures of TFI extracted from the PK surveys database. Results from the estimation of propensity scores based on this subsample ranges from 0.0001 to 0.5 for the non-DEPHY group and from 0.001 to 0.77 for the DEPHY group. Figure 4 shows that the density distributions of propensity scores by groups. We perform full mahalanobis covariate and propensity score matching with two nearest neighbors and with robust Abadie–Imbens standard errors (Abadie et al., 2004; Abadie and Imbens, 2006). The corresponding balancing tests are provided in Appendix D.

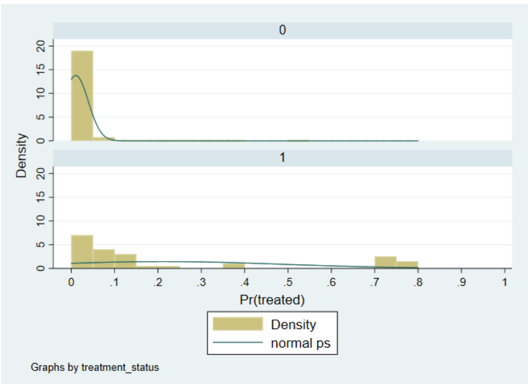

Figure 4: Density of propensity scores by group.

Table 4 gives the estimated ATT from the 2-nearest neighbors DID matching estimator based on propensity score. The estimator in column 1 is slightly less precise (different from zero at 5% level of significance) than our previous estimates. Figure 5 gives a

Table 4: Treatment effects using 2-nearest neighbors DID matching procedures based on propensity score.

Dependent variable Estimation method	TFI(1) DID matching	TFI(2) w/t BC DID matching	TFI(2) BC DID matching	TFI(2) w BC DID matching	TFI(1) Matching
ATT	-2,16	-1,64	1,28	-0,36	-4,95
Standard errors	0,81	0,69	0,26	0,61	0,97
Nb. of treated	40	40	40	40	31
Nb. of controls	3091	3091	3091	3091	4390
Min nb. of neighbors	2	2	2	2	2
Max nb. of neighbors	3	3	3	3	3

Notes: Columns 1 and 5 consider the TFI calculated according to our rules (1) whereas columns 2 consider its counterpart calculated by the Department of Statistics of the Ministry of Agriculture (2). Column 5 display the cross sectional matching estimator. This latter is based on a subsample of 31 cropping systems coming from the Agrosyst database which correspond to the 40 parcels coming from the Agreste database, in order to avoid a change in methodology and to yield comparable estimates. Columns 3 and 4 consider respectively the TFI for BC products only and the total TFI including BC products, both calculated by the Department of Statistics of the Ministry of Agriculture (2).

representation of both DID matching and cross sectional matching estimators with their confidence intervals. Column 1 shows a negative difference in TFI of 2.16 points between DEPHY and control groups. Given that the average TFI equals 11.41 in the DEPHY group, it would have been 13.57 (11.41+2.16) in the absence of the program. It means that the program reduces the average TFI by 16% in DEPHY vineyards. Compared to our previous findings, it suggest that cross sectional matching estimators are prone to selection bias caused by unobserved time-invariant characteristics. A comparison with the cross sectional matching estimator based on this subsample (-4.97) confirms it. Furthermore, the TFI for BC products increased by 77% (2.94-1.28) in the DEPHY group and the total TFI (including BC products) did not decrease significantly. It reveals a large substitution phenomenon between these two groups of products.

In any case, this estimation provides an estimate of the magnitude of selection bias caused by unobserved time-invariant characteristics that is not addressed by the matching. Figure 6 provides an illustration of this estimation. In addition, results from the 2-nearest

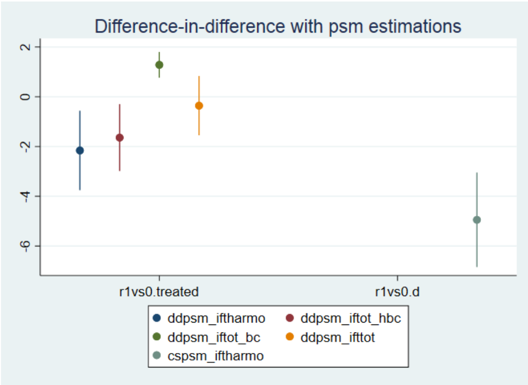

Figure 5: 2-nearest neighbors DID matching (on the left) and cross sectional matching (on the right) estimators based on propensity score and their confidence intervals.

neighbors DID matching estimator based on vectors of covariates are in Appendix C.

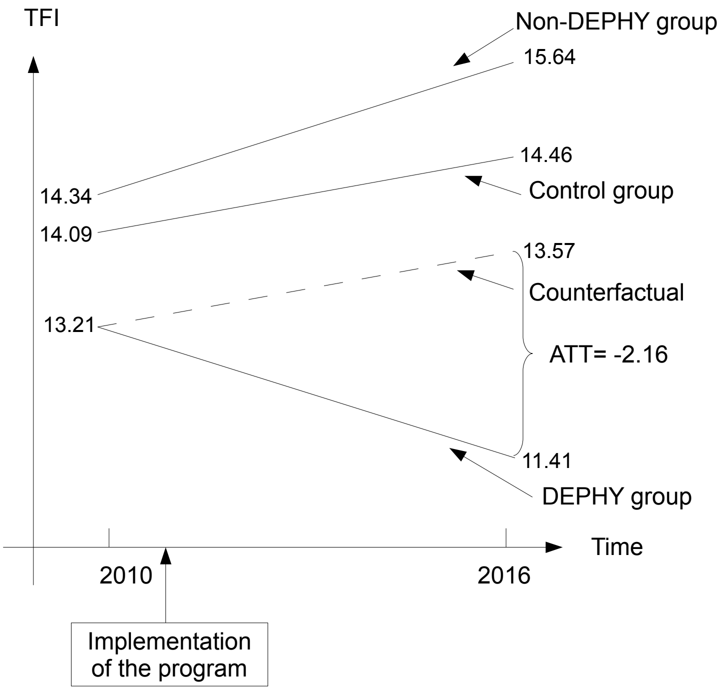

Figure 6: Illustration of the DID matching estimation

Combining DID with matching is consistent if matching also is. Given that the matching quality is not fully satisfying, we complete our sensitivity analysis by applying a DID procedure on the totality of our sample. Results are presented in Appendix C. The

DID estimator indicates a significant negative difference of 3.08 between the DEPHY and control groups. It suggests that the program encourages a reduction in TFI by 21% (11.32+3.08) in DEPHY vineyards. The DID matching and DID analysis confirm the results of the matching procedure. Hence, the result is clear and robust: vineyards participating in the DEPHY network are actually effective in reducing pesticide use, and siginificant reductions has been achieved thanks to the program.

5. Conclusion

The purpose of this work was to estimate, at the microeconometric level, the additional effect of participation in the DEPHY network on pesticide use in the wine growing sector. We offered an approach that deals with self-selection into the newtork using matching and DID procedures. The main results of our analysis suggest that the average TFI of DEPHY vineyards ranges from 16 to 31% below what it would have been used without the DEPHY program. We contribute to the debate over public policies promoting pesticide use reduction and improve the understanding of farmer reaction to agricultural extension services. Our results emphasize the effectiveness of a collective approach on farmers' pesticide use reduction. Given the crucial role of the network engineer in the implementation of pesticide reduction projects, further analysis on potential heterogeneity in the treatment effects depending on the engineer is needed. Given that interferences between DEPHY and non-DEPHY vineyards can be spotted, diffusion effects can be estimated to evaluate the capacity of the network to disseminate information and modify farmers' attitudes towards uncertainty. The findings of this paper can be compared to the effectiveness of AES specifically targeting the use of pesticides in French vineyards. The quantity of herbicides used by participants in such schemes are about 40-50% below what they would have used without AES(Kuhfuss and Subervie, 2018). Hence, the complementarity or substitutability between the DEPHY program and AES is of interest and must be further investigated. Finally, this study complements the work of Lechenet *et al.*(Lechenet et al., 2017) which suggested that pesticide use could be reduced by 42% in 59% of DEPHY farms without productivity and profitability loss. Additional work is necessary to measure the impact of the DEPHY program on yields, nonetheless, the target set by the French government appears elusive. To conclude, vineyards participating in the DEPHY network are actually effective in reducing pesticide use. The adoption of low-pesticide production systems can be fostered through crop-specific and region-specific collective programs including the support of a technical engineer. Hence, targets of pesticide use reduction must be set according to the farming context and to the technical options available.

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References

(2018). Indicateur de fréquence de traitements phytopharmaceutiques (IFT), guide méthodologique. Technical report, Ministere de l'Agriculture et de l'Alimentation.

Abadie, A., Imbens, G., Drukker, D., and Leber Herr, J. (2004). Implementing matching estimators for average treatment effects in stata. *Stata Journal*, 4:290–311.

Abadie, A. and Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica*, 74(1):235–267.

Andert, S., Bürger, J., Stein, S., and Gerowitt, B. (2016). The influence of crop sequence on fungicide and herbicide use intensities in north german arable farming. *European Journal of Agronomy*, 77:81–89.

Aubertot, J.-N., Barbier, J. M., Carpentier, A., Gril, J.-N., Guichard, L., Lucas, P., Savary, S., and VOLTZ, M. (2007). *Pesticides, agriculture et environnement. Réduire l'utilisation des pesticides et en limiter les impacts environnementaux. Expertise scientifique collective Inra-Cemagref (décembre 2005).* Expertises Collectives.

Bailey, A. S., Bertaglia, M., Fraser, I. M., Sharma, A., and Douarin, E. (2009). Integrated pest management portfolios in UK arable farming: results of a farmer survey. *Pest Management Science*, 65(9):1030–1039.

Beckmann, V. and Wesseler, J. (2003). How labour organization may affect technology adoption: an analytical framework analysing the case of integrated pest management. *Environment and Development Economics*, 8(3):437–450.

Caliendo, M. and Kopeinig, S. (2005). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1):31–72.

Chabé-Ferret, S. and Subervie, J. (2013). How much green for the buck? Estimating additional and windfall effects of french agro-environmental schemes by did-matching. *Journal of Environmental Economics and Management*, 65(1):12–27.

EU (2005). Regulation (EC) no 396/2005 on maximum residue levels of pesticides in or on food and feed of plant and animal origin.

EU (2009a). Directive 2009/127/EC amending directive 2006/42/ec with regard to machinery for pesticide application.

EU (2009b). Directive 2009/128/EC of the european parliament and of the council of 21 october 2009 establishing a framework for community action to achieve the sustainable use of pesticides.

EU (2009c). Regulation (EC) no 1107/2009 concerning the placing of plant protection products on the market.

EUROSTAT (2018). Agri-environmental indicator - consumption of pesticides.

Gaba, S., Gabriel, E., Chadœuf, J., Bonneu, F., and Bretagnolle, V. (2016). Herbicides do not ensure for higher wheat yield, but eliminate rare plant species. *Scientific Reports*, 6:30112.

Gianessi, L., Rury, K., and Rinkus, A. (2009). An evaluation of pesticide use reduction policies in scandinavia. *Outlooks on Pest Management*, 20:268–274.

Hossard, L., Philibert, A., Bertrand, M., Colnenne-David, C., Debaeke, P., Munier-Jolain, N., Jeuffroy, M. H., Richard, G., and Makowski, D. (2014). Effects of halving pesticide use on wheat production. *Scientific Reports*, 4:4405.

Imbens, G. W. and Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1):5–86.

Jacquet, F., Butault, J.-P., and Guichard, L. (2011). An economic analysis of the possibility of reducing pesticides in french field crops. *Ecological Economics*, 70(9):1638 – 1648.

Kudsk, P. and Jensen, J. (2014). Experiences with implementation and adoption of integrated pest management in denmark. *Integrated Pest Management*, pages 467–486.

Kuhfuss, L. and Subervie, J. (2018). Do European Agri-environment Measures Help Reduce Herbicide Use? Evidence From Viticulture in France. *Ecological Economics*, 149(C):202–211.

Lamichhane, J. R., Dachbrodt-Saaydeh, S., Kudsk, P., and Messéan, A. (2015). Toward a reduced reliance on conventional pesticides in european agriculture. *Plant Disease*, 100(1):10–24.

Lechenet, M., Dessaint, F., Py, G., Makowski, D., and Munier-Jolain, N. (2017). Reducing pesticide use while preserving crop productivity and profitability on arable farms. *Nature Plants*, 3:17008.

Lefebvre, M., Langrell, S. R. H., and Gomez-y Paloma, S. (2015). Incentives and policies for integrated pest management in Europe: A review. *Agronomy for Sustainable Development*, 35(1):27–45.

Mailly, F., Hossard, L., Barbier, J.-M., Thiollet-Scholtus, M., and Gary, C. (2017). Quantifying the impact of crop protection practices on pesticide use in wine-growing systems. *European Journal of Agronomy*, 84:23 – 34.

Musser, W. N., Tew, B. V., and Epperson, J. E. (1981). An economic examination of an integrated pest management production system with a contrast between E-V and stochastic dominance analysis. *Journal of Agricultural and Applied Economics*, 13(1):119–124.

Nave, S., Jacquet, F., and Jeuffroy, M.-H. (2013). Why wheat farmers could reduce chemical inputs: evidence from social, economic, and agronomic analysis. *Agronomy for Sustainable Development*, 33(4):795–807.

Neumeister, L. (2007). Pesticide use reduction strategies in europe, six case studies.

Östman, Ö., Ekbom, B., and Bengtsson, J. (2003). Yield increase attributable to aphid predation by ground-living polyphagous natural enemies in spring barley in Sweden. *Ecological Economics*, 45(1):149–158.

Petit, S., Munier-Jolain, N., Bretagnolle, V., Bockstaller, C., Gaba, S., Cordeau, S., Lechenet, M., Mézière, D., and Colbach, N. (2015). Ecological intensification through pesticide reduction: Weed control, weed biodiversity and sustainability in arable farming. *Environmental Management*, 56(5):1078–1090.

Petit Michaut, S., Auguste, C., Biju-Duval, L., Charalabidis, A., Ducourtieux, C., Labruyère, S., Ricci, B., Trichard, A., and Bohan, D. (2015). La prédation des graines d'adventices par les coléoptères carabidae.

Ray, D. K., Ramankutty, N., Mueller, N. D., West, P. C., and Foley, J. A. (2012). Recent patterns of crop yield growth and stagnation. *Nature Communications*, 3:1293.

Reau, R., Mischler, P., and Petit, M.-S. (2010). Evaluation au champ des performances de systèmes innovants en cultures arables et apprentissage de la protection intégrée en fermes pilotes.

Rosenbaum, P. R. and Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39(1):33–38.

Rosenzweig, C., Iglesias, A., Yang, X., R. Epstein, P., and Chivian, E. (2001). Climate change and extreme weather events; implications for food production, plant diseases, and pests. *Global Change and Human Health*, 2:90–104.

Rubin, D. B. (1978). Bayesian inference for causal effects: The role of randomization. *The Annals of Statistics*, 6(1):34–58.

Waterfield, G. and Zilberman, D. (2012). Pest management in food systems: An economic perspective. *Annual Review of Environment and Resources*, 37(1):223–245.

Wilson, C. and Tisdell, C. (2001). Why farmers continue to use pesticides despite environmental, health and sustainability costs. *Ecological Economics*, 39(3):449–462.

Appendix A. Details on the construction of TFI

This section describes the methodology for calculating TFI. We apply the main rules coming from the TFI methodological handbook of the Ministry of Agriculture (agr, 2018).

Appendix A.1. 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:

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

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.

Appendix A.2. 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.

Appendix A.3. Adjustments

The adjustments concern three types of situations: - TFI of a treatment can not 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.

Appendix B. Sources and definition of the variables

Table B.5: Sources and definitions of the variables

Variable	Definition	Source
Dependent variable		
TFI	Treatment Frequency Index	Agreste - PK surveys 2010, 2016 Agrosyst - DEPHY network 2011-2016
Treatment variable		
Participation in the Dephy network	Dummy variable equal to 1 if the cropping system i is in the DEPHY netowrk.	Agrosyst - DEPHY network 2011-2016
Covariates		
Date of birth	Date of birth of the manager.	Agreste - Agricultural Census 2010
Sex	Dummy variable equal to 1 if the manager is a male and 2 otherwise.	Agreste - Agricultural Census 2010
Baccalaureat	Dummy variable equal to 1 if the manager has a general/agricultural Baccalaureat	Agreste - Agricultural Census 2010
No baccalaureat	Dummy variable equal to 1 if the manager has a no general/agricultural Baccalaureat (excluded)	Agreste - Agricultural Census 2010
Spouse's activity: Agricultural	Dummy variable equal to 1 if the manager's spouse is employed in the agricultural sector	Agreste - Agricultural Census 2010
Spouse's activity: Non agricultural	Dummy variable equal to 1 if the manager's spouse is employed outside the agricultural sector	Agreste - Agricultural Census 2010

Table B.6: Sources and definitions of the variables

Variable	Definition	Source
Covariates		
Spouse's activity: None	Dummy variable equal to 1 if the manager's spouse is not employed (excluded)	Agreste - Agricultural Census 2010
On-farm labour	Total on-farm labour in annual work units	Agreste - Agricultural Census 2010
Individual farmer	Dummy variable equal to 1 if the vineyard's legal status is "Individual farmer" (excluded)	Agreste - Agricultural Census 2010
Farmer association	Dummy variable equal to 1 if the vineyard's legal status is not "Individual farmer"	Agreste - Agricultural Census 2010
Ownership	Ownership as a share of the UAA	Agreste - Agricultural Census 2010
Insurance	Dummy variable equal to 1 in case of adhesion to an insurance package	Agreste - Agricultural Census 2010
Solidarite	Dummy variable equal to 1 in case of adhesion to a solidarity mechanism for environmental and sanitary risks	Agreste - Agricultural Census 2010
Diversification	Dummy variable equal to 1 in case of diversification activities	Agreste - Agricultural Census 2010
Production	in hectoliters per hectare	Agreste - Agricultural Census 2010
AOP/IGP production	Protected Denomination of Origin and Protected Geographical Indication as a share of the production	Agreste - Agricultural Census 2010
Local distribution network	Dummy variable equal to 1 if part of the production is sold via local distribution network	Agreste - Agricultural Census 2010
Sprayer calibration	Dummy variable equal to 1 if the sprayer's flow has been adjusted	Agreste - Agricultural Census 2010

Table B.7: Sources and definitions of the variables

Variable	Definition	Source
Covariates		
% of production in local distribution network	Proportion of the production in local distribution network is 0 or below 10% (=5), or between 10 and 50% (=30), or between 50 and 75% (=62) or above 75% (=87)	Agreste - Agricultural Census 2010
External treatments	Dummy variable equal to 1 if pesticide treatments are the most frequently carried out by cooperatives for the use of agricultural equipment or specialized companies	Agreste - Agricultural Census 2010
Internal treatments	Dummy variable equal to 1 if pesticide treatments are the most frequently carried out internally (excluded)	Agreste - Agricultural Census 2010
UAA	Utilized Agricultural Area in ares	Agreste - Agricultural Census 2010
Vineyard surface area	Vineyard surface in ares	Agreste - Agricultural Census 2010
% of Vineyard surface	Vineyard surface as a share of the UAA	Agreste - Agricultural Census 2010
% Organic farming surface	Organic farming surface as a share of the UAA	Agreste - Agricultural Census 2010
UAA without pesticide	Proportion of UAA cultivated without pesticide	Agreste - Agricultural Census 2010
Organic conversion	Dummy variable equal to 1 if a conversion to organic within 5 years is planned	Agreste - Agricultural Census 2010
Organic farming	Dummy variable equal to 1 if wine grapes are organically grown for the cropping system of interest	Agreste - PK surveys 2010 Agrosyst - DEPHY network 2010-2015
Grassing	Dummy variable equal to 1 if grassing is used for the cropping system of interest	Agreste - PK surveys 2010 Agrosyst - DEPHY network 2010-2015
Carignan	Dummy variable equal to 1 if the Carignan variety is grown for the cropping system of interest	Agreste - PK surveys 2010 Agrosyst - DEPHY network 2010-2015

Table B.8: Summary statistics for the sample.

Variable	Observations	Mean	Standard Deviation	Min	Max
TFI	4530	15,09	5,84	0,13	47,02
On-farm labour	4530	4742,67	6799,95	125	90083,33
Insurance	4530	0,49	0,50	0	1
Solidarite	4530	0,05	0,22	0	1
Local distribution network	4530	0,49	0,50	0	1
% of production in local distribution network	4530	1,18	7,81	0	87
Diversification	4530	0,17	0,37	0	1
Organic conversion	4530	0,08	0,26	0	1
Sprayer calibration	4530	0,30	0,46	0	1
Sex	4530	1,17	0,37	1	2
Date of birth	4530	1962,15	10,36	1909	1991
Baccalaureat	4530	0,52	0,50	0	1
Vineyard surface area	4530	2800,51	3506,15	0	51500
Spouse's activity: Agricultural	4530	0,29	0,45	0	1
Spouse's activity: Non-agricultural	4530	0,26	0,44	0	1
% of vineyard surface	4530	0,76	0,30	0	1
Production	4530	0,56	0,30	0	7,40
AOP/IGP production	4530	0,85	0,31	0	1
UAA	4530	4709,91	5694,83	9	55773
Farmer association	4530	0,62	0,49	0	1
Ownership	4530	0,30	0,37	0	1
UAA without pesticide	4530	0,16	0,28	0	1
External treatments	4530	0,07	0,25	0	1
% of organic farming surface	4530	0,06	0,22	0	1
Organic farming	4530	0,07	0,26	0	1
Grassing	4530	0,49	0,50	0	1
Carignan	4530	0,03	0,17	0	1

Table B.9: Summary statistics for the DEPHY vineyards.

Variable	Observations	Mean	Standard Deviation	Min	Max
TFI	140	10,14	7,22	0,28	32,10
On-farm labour	140	5869,28	6328,72	383,73	45545,96
Insurance	140	0,49	0,50	0	1
Solidarite	140	0,08	0,27	0	1
Local distribution network	140	0,66	0,47	0	1
% of production in local distribution network	140	1,66	8,86	0	87
Diversification	140	0,26	0,44	0	1
Organic conversion	140	0,14	0,35	0	1
Sprayer calibration	140	0,39	0,49	0	1
Sex	140	1,16	0,37	1	2
Date of birth	140	1965,49	8,74	1945	1983
Baccalaureat	140	0,81	0,40	0	1
Vineyard surface area	140	3531,28	5492,12	200	43000
Spouse's activity: Agricultural	140	0,33	0,47	0	1
Spouse's activity: Non-agricultural	140	0,32	0,47	0	1
% of vineyard surface	140	0,83	0,26	0,07	1
Production	140	0,52	0,27	0	1,27
AOP/IGP production	140	0,82	0,35	0	1
UAA	140	4729,34	6603,70	200	49850
Farmer association	140	0,81	0,40	0	1
Ownership	140	0,19	0,31	0	1,00
UAA without pesticide	140	0,18	0,34	0	1
External treatments	140	0,01	0,12	0	1
% of organic farming surface	140	0,13	0,32	0	1
Organic farming	140	0,16	0,37	0	1
Grassing	140	0,90	0,30	0	1
Carignan	140	0,05	0,22	0	1

Table B.10: Summary statistics for the non-DEPHY vineyards.

Variable	Observations	Mean	Standard Deviation	Min	Max
TFI	4390	15,24	5,72	0,13	47,02
On-farm labour	4390	4706,75	6812,05	125	90083,33
Insurance	4390	0,48	0,50	0	1
Solidarite	4390	0,05	0,22	0	1
Local distribution network	4390	0,49	0,50	0	1
% of production in local distribution network	4390	1,16	7,78	0	87
Diversification	4390	0,16	0,37	0	1
Organic conversion	4390	0,07	0,26	0	1
Sprayer calibration	4390	0,30	0,46	0	1
Sex	4390	1,17	0,37	1	2
Date of birth	4390	1962,05	10,40	1909	1991
Baccalaureat	4390	0,51	0,50	0	1
Vineyard surface area	4390	2777,21	3422,33	0	51500
Spouse's activity: Agricultural	4390	0,29	0,45	0	1
Spouse's activity: Non-agricultural	4390	0,26	0,44	0	1
% of vineyard surface	4390	0,75	0,31	0	1
Production	4390	0,56	0,30	0	7,40
AOP/IGP production	4390	0,85	0,31	0	1
UAA	4390	4709,29	5664,31	9	55773
Farmer association	4390	0,62	0,49	0	1
Ownership	4390	0,31	0,37	0	1
UAA without pesticide	4390	0,16	0,28	0	1
External treatments	4390	0,07	0,25	0	1
% of organic farming surface	4390	0,06	0,22	0	1
Organic farming	4390	0,07	0,26	0	1
Grassing	4390	0,48	0,50	0	1
Carignan	4390	0,03	0,17	0	1

Appendix C. Additional results

Table C.11: Results of logit participation model based on a sample of 5430 winegrowers and used for the cross sectional matching procedure.

Variable	Coefficient
On-farm labour	-3.38e-06
	(0.729)
Insurance	-0.0587
	(0.750)
Solidarite	0.720**
	(0.0404)
Local distribution network	0.326
	(0.128)
% of production in local distribution network	-0.00248
	(0.797)
Diversification	0.484**
	(0.0464)
Organic conversion	0.448
	(0.114)
Sprayer calibration	0.419**
	(0.0276)
Sex	0.0203
	(0.933)
Date of birth	0.0251***
	(0.00913)
Baccalaureat	1.003***
	(1.26e-05)
Vineyard surface area	8.43e-05
	(0.246)
Spouse's activity: Agricultural	0.450*
	(0.0507)
Spouse's activity: Non-agricultural	0.407*
	(0.0723)
% of vineyard surface	0.930
	(0.142)
Production	-0.542
	(0.195)
AOP/IGP production	-0.858***
	(0.00501)
UAA	-5.50e-05
	(0.332)
Farmer association	0.294
	(0.226)
Ownership	-0.585**
	(0.0480)
UAA without pesticide	-0.0299
	(0.938)
External treatments	-1.133
	(0.126)
% of organic farming surface	-0.00174
	(0.998)
Organic farming	0.674
	(0.227)
Grassing	2.336***
	(0)
Carignan	1.167***
	(0.00754)
Constant	-55.68***
	(0.00334)
Observations	4,530

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.12: Results of logit participation model based on a sample of 3131 winegrowers and used for the DID matching procedure.

Variable	Coefficients
On-farm labour	1.15e-05
	(0.399)
Insurance	-0.166
	(0.657)
Solidarite	1.522***
	(0.00661)
Local distribution network	0.161
	(0.710)
% of production in local distribution network	-0.0784
	(0.563)
Diversification	-1.231**
	(0.0355)
Organic conversion	1.273**
	(0.0120)
Sprayer calibration	0.928**
	(0.0255)
Sex	-0.312
	(0.624)
Date of birth	0.0467**
	(0.0218)
Baccalaureat	0.962**
	(0.0452)
Vineyard surface area	0.000161**
	(0.0375)
Spouse's activity: Agricultural	-0.0400
	(0.944)
Spouse's activity: Non-agricultural	0.0903
	(0.829)
% of vineyard surface	1.688
	(0.117)
Production	0.197
	(0.563)
AOP/IGP production	-1.852***
	(0.00129)
UAA	-5.08e-05
	(0.445)
Farmer association	0.0119
	(0.983)
Ownership	-1.448**
	(0.0169)
UAA without pesticide	-0.481
	(0.561)
External treatments	-0.328
	(0.732)
% of organic farming surface	-0.514
	(0.689)
Organic farming	1.572
	(0.167)
Grassing	4.129***
	(0.000268)
Carignan	0.701
	(0.423)
Constant	-100.7**
	(0.0132)
Observations	3,131

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.13: Treatment effects using the 2-nearest neighbors DID matching procedure based on vector of covariates.

Dependent variable Estimation method	TFI(1) DID matching	TFI(2) w/t BC DID matching	TFI(2) BC DID matching	TFI(2) w BC DID matching	TFI(1) Matching
ATT	-1,80	-2,52	1,15	-1,37	-4,44
Standard errors	1,36	0,99	0,39	0,97	1,28
Nb. of treated	40	40	40	40	31
Nb. of controls	3091	3091	3091	3091	4390
Min nb. of neighbors	2	2	2	2	2
Max nb. of neighbors	4	4	4	4	3

Notes: Columns 1 and 5 consider the TFI calculated according to our rules (1) whereas column 2 consider its counterpart calculated by the Department of Statistics of the Ministry of Agriculture (2). Column 5 display the cross sectional matching estimator based on this subsample. Columns 3 and 4 consider respectively the TFI for BC products only and the total TFI including BC products, both calculated by the Department of Statistics of the Ministry of Agriculture (2).

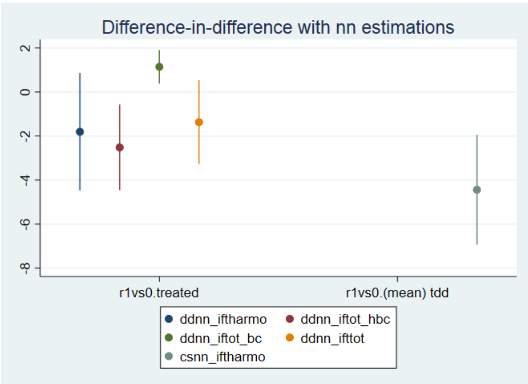

Figure C.7: 2-nearest neighbors DID matching (on the left) and cross sectional matching (on the right) estimators based on vectors of covariates and their confidence intervals.

Table C.14: Treatment effects using a DID procedure

Dependent variable	TFI(1)	TFI(2) w/t BC	TFI(2) BC	TFI(2) w BC
ATT	-3,10	-2,31	1,12	-1,19
Standard errors	1,06	0,88	0,38	0,94
Nb. of treated	41	41	41	41
Nb. of controls	3131	3131	3131	3131

Notes: Columns 1 and 5 consider the TFI calculated according to our rules (1) whereas column 2 consider its counterpart calculated by the Department of Statistics of the Ministry of Agriculture (2). Column 5 display the cross sectional matching estimator based on this subsample. Columns 3 and 4 consider respectively the TFI for BC products only and the total TFI including BC products, both calculated by the Department of Statistics of the Ministry of Agriculture (2).

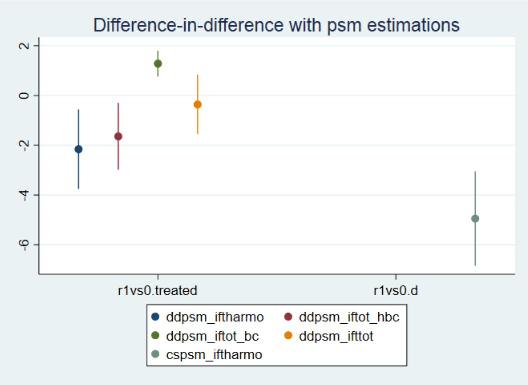

Figure C.8: DID estimators for various versions of the TFI and their confidence intervals.

Appendix D. Balancing tests

Table D.15: Balancing test before and after the 1-nearest neighbor matching procedure based on propensity score.

	Normalized differences	
	Raw	Matched
On-farm labour	0,18	0,23
Insurance	0,02	-0,17
Solidarite	0,11	0,08
Local distribution network	0,37	-0,16
% of production in local distribution network	0,06	-0,01
Diversification	0,25	0,05
Organic conversion	0,22	0,02
Sprayer calibration	0,19	0,04
Sex	-0,01	0,06
Date of birth	0,36	0,01
Baccalaureat	0,65	-0,06
Vineyard surface area	0,16	0,17
Spouse's activity: Agricultural	0,09	0,02
Spouse's activity: Non-agricultural	0,14	-0,05
% of vineyard surface	0,25	-0,03
Production	-0,13	0,13
AOP/IGP production	-0,11	-0,10
UAA	0,00	0,17
Farmer association	0,43	0,00
Ownership	-0,34	0,01
UAA without pesticide	0,08	-0,11
External treatments	-0,27	0,00
% of organic farming surface	0,26	-0,10
Organic farming	0,29	-0,02
Grassing	1,02	0,00
Carignan	0,11	0,00

Note: Column 1 reports the normalized mean differences between the treated group and the untreated group. Column 2 reports the normalized mean differences between the treated and the winegrowers from the untreated group who were selected in the matching procedure using a minimum of 1 nearest neighbor and based on propensity score. The normalized difference is the difference in means between the two groups considered divided by the square root of the sum of variances for both groups. Nb. of observations: 4530.

Table D.16: Pre-treatment characteristics for the groups used for the 1-nearest neighbor matching procedure based on vector of covariates.

	Normalized differences	
Variable	Raw	Matched
On-farm labour	0,18	0,09
Insurance	0,02	-0,04
Solidarite	0,11	0,00
Local distribution network	0,37	-0,05
% of production in local distribution network	0,06	0,03
Diversification	0,25	0,07
Organic conversion	0,22	-0,02
Sprayer calibration	0,19	0,04
Sex	-0,01	0,06
Date of birth	0,36	0,13
Baccalaureat	0,65	0,15
Vineyard surface area	0,16	0,06
Spouse's activity: Agricultural	0,09	-0,02
Spouse's activity: Non-agricultural	0,14	0,02
% of vineyard surface	0,25	-0,03
Production	-0,13	0,07
AOP/IGP production	-0,11	-0,06
UAA	0,00	0,07
Farmer association	0,43	-0,09
Ownership	-0,34	0,05
UAA without pesticide	0,08	0,03
External treatments	-0,27	0,00
% of organic farming surface	0,26	0,01
Organic farming	0,29	0,00
Grassing	1,02	0,30
Carignan	0,11	0,00

Note: Column 1 reports the normalized mean differences between the treated group and the untreated group. Column 2 reports the normalized mean differences between the treated and the winegrowers from the untreated group who were selected in the matching procedure using a minimum of 1 nearest neighbor and based on vector of covariates. The normalized difference is the difference in means between the two groups considered divided by the square root of the sum of variances for both groups. Nb. of observations: 4530.

Table D.17: Balancing test before and after the 2-nearest neighbors DID matching procedure based on propensity score.

Variable	Normalized differences Raw	Matched
On-farm labour	0,64	0,16
Insurance	0,19	-0,02
Solidarite	0,23	0,00
Local distribution network	0,20	-0,20
% of production in local distribution network	-0,18	-0,24
Diversification	-0,21	-0,19
Organic conversion	0,44	-0,32
Sprayer calibration	0,34	0,22
Sex	-0,29	0,25
Date of birth	0,33	0,12
Baccalaureat	0,71	0,40
Vineyard surface area	0,67	-0,07
Spouse's activity: Agricultural	-0,21	-0,31
Spouse's activity: Non-agricultural	0,20	-0,01
% of vineyard surface	0,40	0,25
Production	0,14	-0,06
AOP/IGP production	-0,33	-0,24
UAA	0,57	-0,11
Farmer association	0,58	-0,07
Ownership	-0,40	0,43
UAA without pesticide	-0,20	0,13
External treatments	-0,22	-0,07
% of organic farming surface	0,10	0,02
Organic farming	0,22	0,05
Grassing	1,41	0,00
Carignan	-0,06	0,00

Note: Column 1 reports the normalized mean differences between the treated group and the untreated group. Column 2 reports the normalized mean differences between the treated and the winegrowers from the untreated group who were selected in the DID matching procedure using a minimum of 2 nearest neighbors and based on propensity score. The normalized difference is the difference in means between the two groups considered divided by the square root of the sum of variances for both groups. Nb. of observations: 3131.

Table D.18: Balancing test before and after the 2-nearest neighbors DID matching procedure based on vector of covariates.

	Normalized differences	
	Raw	Matched
On-farm labour	0,64	0,29
Insurance	0,19	0,12
Solidarite	0,23	0,09
Local distribution network	0,20	-0,21
% of production in local distribution network	-0,18	-0,31
Diversification	-0,21	-0,36
Organic conversion	0,44	-0,17
Sprayer calibration	0,34	0,19
Sex	-0,29	-0,09
Date of birth	0,33	0,11
Baccalaureat	0,71	0,07
Vineyard surface area	0,67	0,20
Spouse's activity: Agricultural	-0,21	-0,15
Spouse's activity: Non-agricultural	0,20	0,10
% of vineyard surface	0,40	-0,04
Production	0,14	0,22
AOP/IGP production	-0,33	-0,17
UAA	0,57	0,23
Farmer association	0,58	0,09
Ownership	-0,40	-0,01
UAA without pesticide	-0,20	0,02
External treatments	-0,22	0,00
% of organic farming surface	0,10	0,01
Organic farming	0,22	0,00
Grassing	1,41	0,48
Carignan	-0,06	0,00

Note: Column 1 reports the normalized mean differences between the treated group and the untreated group. Column 2 reports the normalized mean differences between the treated and the winegrowers from the untreated group who were selected in the DID matching procedure using a minimum of 2 nearest neighbors and based on vector of covariates. The normalized difference is the difference in means between the two groups considered divided by the square root of the sum of variances for both groups. Nb. of observations: 3131.