Does crop insurance lead to better environmental practices? Evidence from French farms

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Abstract:

The purpose of this paper is to examine how crop insurance influences pesticide use, the two decisions being strategic for risk management at the farm scale. Using data from the Farm Accountancy Data Network (FADN), we consider French farms which cultivate field crops and wine-growing, the two main sectors that participate the most to crop insurance and that use intensively pesticides. The paper implements propensity score matching, difference-in-differences models and a combination of these two methods in order to compare populations of insured and non-insured farmers. The analysis is performed between 2008 and 2012 given a strategic change in the crop insurance system in 2010 that strongly incites farmers to purchase crop insurance with private companies. At the same time, pesticide use was progressively discouraged through public policies. Estimations show that while pesticide use decreases for all crops, the purchase of crop insurance policies softens this reduction for field crops and fasten it for wine-growing. These results emphasize a possible substitutability between crop insurance and pesticides as risk management tools.

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Keywords: Crop insurance, Pesticides, France, FADN

1. Introduction

Crop insurance is a risk management tool aimed at protecting farm yields. Among the strategies used to manage farm risk, this instrument is one of the most widespread given that it compensates losses due to the action of unfavorable weather conditions. In practice, insurance provides claims if the yield falls below a threshold defined in the contract, thus providing significant revenue stabilization over the years (Bielza et al., 2009).

Successive reforms of crop insurance in France have led to an increase in the number and size of farms insured. 2 critical steps occurred: in 2005 when crop insurance was generalized to a wide set of crops and hazards and in 2010 when crop insurance was considered by the government as the principal instrument to manage crop yield risks (Enjolras and Sentis, 2011).

Among available risk management tools at their disposal, farmers also use chemical inputs for the protection of the growth of crops (Horowitz and Lichtenberg, 1994). Pesticides are mainly targeted to control intra-annual pest attacks. By preserving the production, they may also contribute to increase expected yields (Babcock and Hennessy, 1996). Despite the advantages they procure, pesticides generate major issues in terms of danger for farmers (Antle et al., 1998), consumers (Pan et al., 2010) and the environment (Craven and Hoy, 2005).

However, the reduction of pesticide use appears to be a complex issue given their key role for most farmers (Böcker and Finger, 2017). The challenge is major for France given this country is the leading European consumer of chemical inputs and the third largest consumer worldwide (Aubertot et al., 2005). Many differences exist among crops: while arable crops represent 48% of chemical inputs expenditure, they account for only one third of the land farmed (Baschet and Pingault, 2009). Winegrowing accounts for 14% of chemical inputs expenditure but represents only 4% of the land farmed. In 2008, the government decided to reduce consumption by 50% by 2018 within the implementation of EcoPhyto I framework (Butault *et al*., 2011). This ambitious objective was delayed to 2025 following the "EcoPhyto Report" and the Ecophyto II (2015) framework.

Within its strategic frameworks 2007-2013 and 2014-2020, the European Union has been developing support policies both for green agriculture (Westhoek et al., 2014) and risk management schemes (Bardají et al., 2016). Most of the support is concentrated in the 2nd Pillar which concerns rural development policy. Within this framework, farmers receive subsidies providing they comply with rules related to the environment and health. They also benefit from a subsidization of crop insurance policies in order to encourage them to protect their activity. One has to note that pesticides and insurance are not explicitly considered as potential substitutes within this framework.

Many ways to reduce pesticides have been studied in the literature (Finger et al., 2017). Among them, crop insurance and pesticides have been considered, conceptually speaking, as close substitutes given their effects on yields (Aubert and Enjolras, 2014a; Chakir and Hardelin, 2014; Feinerman et al., 1992; Horowitz and Lichtenberg, 1993; Smith and Goodwin, 1996). However, in practice, the modalities of use of both products are rather different and the balance seems to be in favor of pesticides. Crop insurance needs to be purchased before the season begins in order to avoid information asymmetries while pesticides can be used at any time. Moreover, the cost of insurance seems to be higher than the cost of pesticides despite incentives for promoting the former and reinforced constraints on use for the latter (Aubert and Enjolras, 2014b).

The objective of this paper is to measure the extent to which crop insurance leads to more environmentally-friendly behaviors from farmers. As stated before, a large literature has tackled the link between crop insurance and pesticide use. However, to the best of our knowledge, only one study has tried to measure the long-term consequences of crop insurance purchase on pesticide use (Roberts et al., 2003).

In this paper, we propose to adopt a methodology which compares populations of insured and non-insured farmers. More specifically, we use difference-in-difference methods and propensity score matching because these methods allow to simulate a controlled experiment (Antonakis et al, 2010). They have been used in the literature to measure the effects of crop insurance on debt use (Ifft et al., 2015), on profit (Kuethe and Morehart, 2012; Zhao et al., 2016) and on farm value (Ifft et al., 2014).

We apply these methods to survey data collected from the Farm Accountancy Data Network (FADN). This annual database is representative of the production orientation at the national level of all commercial French farms. For the purpose of the analysis, we select only French farmers that had continuously belonged to the sample from 2008 to 2012. This balanced panel included 31,422 farms for each year, representing a total of 157,109 extrapolated observations over the 5-year period in question.

The paper is organized as follows. Section 2 provides the conceptual framework which considers the link between crop insurance and pesticide use. Section 3 introduces the empirical modeling, providing full details on the sample characteristics and the econometric models. Section 4 presents the results. Section 5 offers some concluding remarks.

2. Conceptual framework

The aim of this section is to develop a framework that addresses the link between crop insurance and pesticides. At first, we present the development of crop insurance in France as well as policies in favor of pesticide reduction.

2.1 The development of crop insurance policies in France

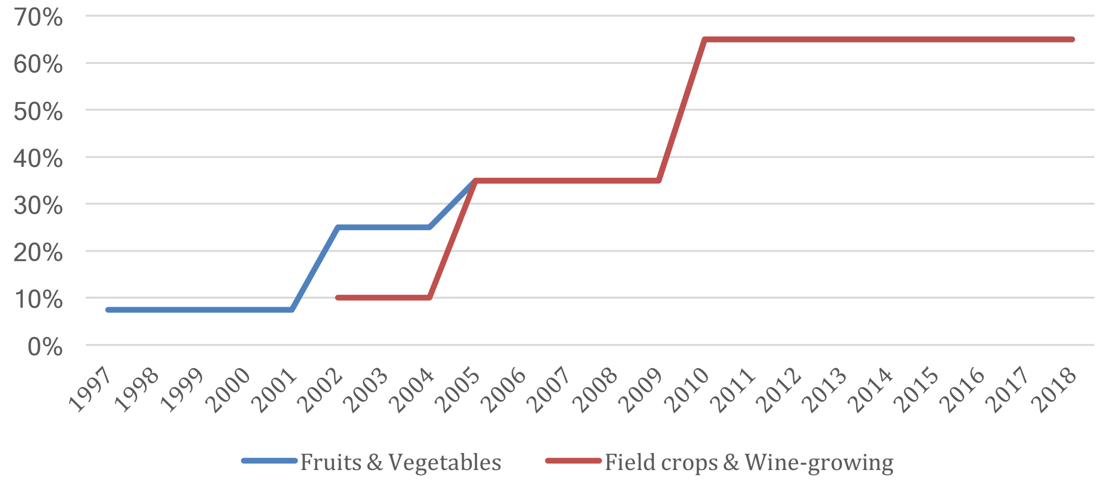
For decades, crop insurance policies have known a regular development in France. In 1964, a National Fund for the Management of Risks in Agriculture (Fonds National de Gestion des Risques en Agriculture, FNGRA) protected for the first time all French farmers against weather risks. Participation to this fund was mandatory and contributions were made by farmers and the government on an equal basis. Before its creation, a compensation was provided on a case-to-case basis.

Modern crop insurance was introduced in 1997 to protect fruit and vegetable yields against hail. At that time, participation was made on a voluntary basis and the government provided a small subsidy (7.5% of the premium). In 2002, the law extended coverage to storms. Moreover, field crops, fruits and wines began to be hedged against hail and frost.

In 2005, the hazards covered through crop insurance policies were extended for all crops to floods, excess of rain and other hazards. At the same time, the subsidy was increased to 35% for all crops but farmers still had the choice to participate to the FNGRA or purchasing private insurance policies. Because the subsidy compensated the increase in crop insurance premiums due to a better hedging, crop insurance became popular. 2 kinds of policies exist: (1) Crop by crop, all plots of a given insured crop have to be included in the policy; (2) At the farm level, the farmer insures more than two crops representing at least 80% of cultivated acreage.

In 2010, the FNGRA stopped hedging hazards that were already covered by private insurance policies. Its mission was therefore centered towards non-insurable hazards and calamities. Since then, French farmers who do not purchase crop insurance cannot receive any public support aimed at compensating losses from the most frequent weather-related hazards. The subsidization rate was increased to 65% (Figure 1).

Figure 1. Evolution of subsidization rates by production



Source: Own representation after data from the French Ministry of Agriculture

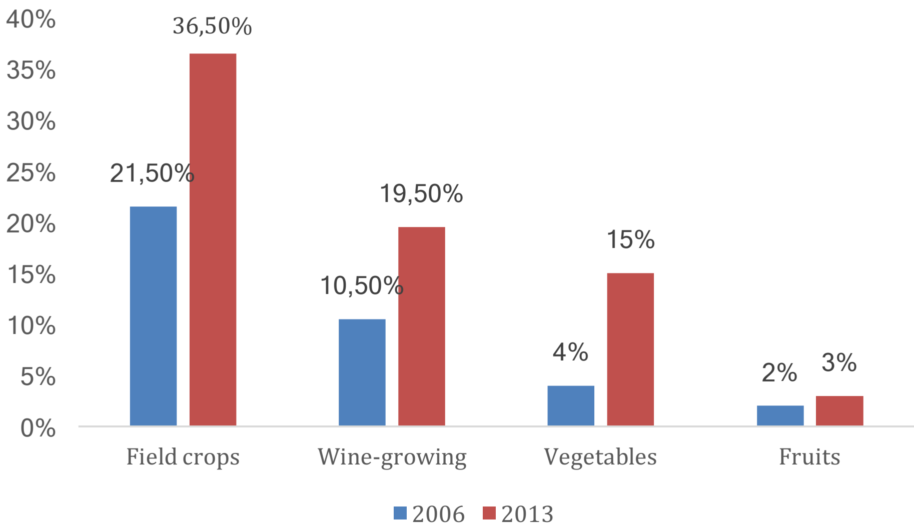
Note: These subsidization rates correspond to the standard rates. Before 2010, rates could be increased for young farmers and for some locations. Since 2015, rates are lowered for some guarantees.

Because this structural change did not strongly boost as expected the market for crop insurance, a baseline crop insurance policy ("contrat socle") was set up in 2015. This policy has replaced until now previous ones. The farmer can choose up to three coverage levels: (1) A first level hedges only against production losses (fixed and variable expenses) at the crop scale, with a subsidy amounting to 65% of the premium. Insurance usually provides indemnity when losses reach a trigger of 30% and with a deductible of 20 to 30% according to the situation. (2) A second level hedges against yield losses at the farm or at the crop scale, by complementing the first level and with a subsidy of 45%. (3) A third level proposes additional guarantees, such as variations in prices and quality losses, without any subsidy.

Over the last years, France has benefitted from the support of the European Union, which finances 75% of crop insurance subsidies, while the national government subsidizes the remaining 25%. Funds come from the 2nd Pillar of the Common Agricultural Policy, which allows for plurennial planning.

As shown by Figure 2, the evolution of insured acreage increased overtime. Field crops appear to be the most insured production, followed by wine-growing and vegetables. By contrast, fruits are not correctly insured, which translates in substantial losses for concerned farmers in case of unfavorable weather conditions. At the moment, the participation is stagnating, which questions the relevancy of the design current crop insurance policies, especially after the introduction of the "contrat socle" (Enjolras and Santeramo, 2016).

Figure 2. Evolution of insured acreage by production between 2006 and 2013



Source: French Ministry of Agriculture

2.2 The literature on crop insurance: a growing body

The literature has extensively examined the issue of farmer participation in crop insurance schemes. In France, Enjolras and Sentis (2011) used data from the Farm Accountancy Data Network (FADN) for years 2003 to 2006. Chakir and Hardelin (2012) conducted a study at the national level on farms located in the department of Meuse between 1993 and 2004. Finger and Lehmann (2012) conducted a similar analysis on Swiss farmers while Santeramo et al. (2016) focused on Italian farmers. In general, in Europe, crop insurance is developing in all countries, with differences in the nature of the risks covered and the proposed contracts (Bardají et al., 2016). These studies mostly emphasize the key role of individual determinants (age and education) as well as structural farm parameters (size and diversification) in the decision to purchase insurance policies.

While the literature on crop insurance is growing, a limited number of studies have focused on the consequences of crop insurance purchase. O'Donoghue et al. (2005) and Yu et al. (2017) showed that crop insurance led to increased size for large farms and increased diversification for all farms. Cornaggia (2013) proved that crop insurance led to enhanced productivity. Deryugina and Konar (2017) showed that crop insurance increased water withdrawal. Ifft et al. (2015) showed that crop insurance is associated with an increase in short-term debt but not long-term debt, which denoted a risk-balancing behavior. Conversely, Uzea et al. (2014) showed that risk management tools did not increase debt use. Ifft et al. (2014) showed that farm value increased when fields are insured. Kuethe and Morehart (2012) proved that crop insurance improved farm-level profit in the United states while Zhao et al. (2016) did not demonstrate such effect in China. By contrast, only one study by Roberts et al. (2003) considered the influence of crop insurance on pesticide use with mixed results according to the crops considered.

2.3 The literature on pesticide use

Pesticide use is a decision which closely depends on the individual strategy of the producer as risk averse farmers are more willing to apply pesticides (Pannell, 1991). Pesticide applications can also be tactical after unfavorable weather conditions prone to crop diseases (Aubert and Enjolras, 2014a; Horowitz and Lichtenberg, 1993; Mishra et al., 2005).

Other key parameter influence pesticide use. Fernandez-Conejo and Ferraioli (1999) and Wu (1999) showed that educated and younger farmers apply less pesticides because they are more aware of their drawbacks. Aubert and Enjolras (2014a) also proved that productive farms and farms located in less-favored areas are more prone to pesticide use.

2.4 Crop insurance and pesticide use: a complex relationship

The literature has long noticed that pesticides share a same goal with crop insurance policies: protecting crop yields (Babcock and Blackmer, 1994; Hall and Norgaard, 1974). For that reason, it has also been noticed that pesticide use and crop insurance purchase may be endogenous, an assumption widely validated by the literature (Babcock and Hennessy, 1996; Chakir and Hardelin, 2010; Goodwin et al., 2004; Wu, 1999). However, as recalled by Aubert and Enjolras (2014a), the decision to take out insurance must be made before the beginning of the season in order to avoid moral hazard effects. By contrast, pesticide use is more flexible.

Nevertheless, the decision to take out crop insurance and to apply pesticides is the farmer’s personal choice. Insurance purchase requires the farmer to pay a premium in exchange for which the insurance company may provide a financial compensation in the event of the partial or total destruction of the harvest. Similarly, inputs involve an expense for the farmer. However, pesticide expenses are more flexible and generally cheaper than insurance expenses (Aubert and Enjolras, 2014b).

Given their fundamental characteristics, pesticides and crop insurance would appear to be substitutable products (Smith and Goodwin, 1996). Crop insurance is traditionally affected by information asymmetries (Just et al., 1999). Opportunistic behaviors and moral hazard have been observed: when insured, farmers may reduce their consumption of chemical inputs (Goodwin et al., 2004). Similarly, farmers demonstrating little risk aversion can consider pesticides and insurance as substitutes (Babcock and Hennessy, 1996). However, pesticide applications may also increase expected yield in favorable years. In this context, pesticides would paradoxically be an additional risk factor, thereby justifying a decision to purchase insurance (Horowitz and Lichtenberg, 1993).

Because both mechanisms provide a sort of certainty equivalent for farmer, the adoption of crop insurance may result in a progressive decrease of pesticides applications and expenses, at least for some crops (Robert et al., 2003).

3. Empirical modelling

3.1 Data

We use a survey of French farmers belonging to the Farm Accountancy Data Network (FADN). This survey is representative of all professional French farms, which reinforces the scope of our results. This sample offers a reliable way to access individual, structural and financial characteristics of professional farms, thereby providing useful information about their expenses. It is then possible to identify the strategies that farmers use to cope with risk (Phimister *et al.*, 2004).

Because of the sampling methodology and more precisely because of the renewal rate, farms belonging to the FADN do not correspond to perennial farms. Within the original databases, we had to select only farms that had continuously belonged to the sample between 2008 and 2012. This period is important because 2008 is three years after the introduction of multi-peril crop insurance policies (in 2005) while 2012 is two years after the government decided not to hedge any more insurable risks (in 2010).

Because of their more intensive use of pesticides and more important participation to crop insurance, we concentrate our analysis to two main Economic and Technical Orientations (ETO): field crops and wine-growing. Our sample finally included 31,422 farms for each year, representing a total of 157,109 extrapolated farms over the 5-year period in question.

Farmers who purchased crop insurance in 2012 represent the treatment group (TG) while farmers not insured in 2012 constitute the control group (CG). There are 5,307 farmers in the TG (3,408 producing field crops and 1,899 wine-growers) and 28,115 farmers in the CG (9,652 producing field crops and 16,463 wine-growers).

Our dependent variable is related to the environmental practices of farmers, measured through pesticide use. Because of the evolution of the physical dimension of the farm between 2008 and 2012, considering the absolute value of pesticide expenses could lead to biased results. An increase in pesticide expenses could translate either the fact that a larger farm needs mechanically more pesticides or that a farm whose cultivated area remains stable increases its applications. Since the amount of pesticide expenses refers to several dimensions, we do not consider the quantity of pesticide but rather the intensity of pesticide use, by dividing the amount of expenses by the cultivated area.

Table 1. List and definition of variables

The list of considered variables is presented in Table 1. In addition to pesticides and crop insurance, we select variables related to the individual characteristics of the farmer (age, education) and the structural characteristics of the farm (gross production, location, specialization).

3.2 Methodology

The impact of insurance policies can be considered as a "treatment" on a group of farms. In order to assess the treatment effect, we have identified a control group, which allows controlling for confounding factors. Ideally, the treated and controlled groups should be randomly assigned to let the effect of treatment be independent from any individual or structural characteristics. Since some farmers decide to adopt crop insurance, we have to control for their characteristics in order to interpret the insurance effect independently from any observed characteristics. Hence, the underlying assumption is that, conditional on observable factors, the treatment and control groups differ only according to the effect of the treatment.

For this reason, three estimation strategies have been set up with the aim to ensure robustness of the results: propensity score matching (PSM), difference-in-differences (DID), and a combination of these techniques (PSM-DID). While trying to measure the effects of insurance on pesticide use, such strategies differ in the construction of the groups and in the measure of the effects (Zhao et al., 2016).

3.2.1 PSM estimates

The PSM has become popular since Rosenbaum and Rubin (1983) who developed a method to simulate a controlled experiment framework for non-randomly assigned groups. Such method allows to specify correctly the CG, by using propensity scores to group observations in accurate CG and TG. Then, the treatment effect on the outcome is perceived by comparing directly across observations in each identified group.

The propensity score is the conditional probability of being treated. In our case study, the treatment is the purchase of crop insurance.

$$P(X_i) = \mathrm{P}(I_i = 1|X_i) = E(I_i|X_i) = X_i\beta + \varepsilon_i \tag{1}$$

Where: $P(X_i)$ is the probability of receiving a treatment, X is the matrix of observable farm and operator characteristics, β is the vector of estimated coefficients, I = 1 if the farmer is insured and 0 otherwise, i = 1,…,n denote farm observations, t is the time and ε is the random error.

$p(X_i)$ is generally estimated through logit models which include observed farmers characteristics (Kott, 1998). Then, this value is used in turn to estimate the average effect of treatment using matching methods (Becker and Ichino, 2002). Each treated farmer is associated a close CG. The effect of the treatment is measured by comparing treated farmers to non-treated ones.

Variables X are selected from previous studies related to pesticide use. They include the operator's age and general education, the gross production of the farm, its location in less-favored areas and its specialization (see Table 1). The aim is to consider all fixed characteristics that let two farmers being in a same category be comparable. Hence, the gross production is not considered in a quantitative way but in a qualitative one. The French Ministry of Agriculture defines three kinds of farms: the small (less than €25,000, not included in our sample), the medium (between €25,000 and €100,000) and the large ones (higher than €100,000)[1].

The impact of crop insurance on pesticide use is then measured at the farm scale by the average treatment effect on the treated (ATT) which can be expressed as:

$$ATT = E(Y_1 - Y_0|P(X), I = 1) = E(Y_1|P(X), I = 1) - E(Y_0|P(X), I = 1) \qquad (2)$$

Where: Y is the outcome variable.

3.2.2 DID and PSM-DID estimates

The difference-in-differences models basically measures the effect of a treatment by differentiating the average outcome for the TG before and after treatment relative to the difference in average outcome in the CG before and after treatment. Such model relies on the assumption that the TG and CG are identical in terms of observable factors. Since these two groups are comparable, the adoption of crop insurance is independent from any individual or structural characteristics. Consequently, the difference between the pre- and post-treatment for the CG accounts for any time-invariant unobservable factors that may confound the effect of treatment on the treated observations. The DID method can therefore identify the average effect of a treatment on the outcome. In our case study, farmers buying insurance are assimilated to the TG while the other farmers belong to the CG. The treatment can be identified with crop insurance purchase at two points in time.

[1] The classification is provided in this official document: http://agreste.agriculture.gouv.fr/IMG/pdf_pbs.pdf

The average treatment effect (ATE) measured using the DID can be expressed as:

$$ATE = \{E[Y|X, I = 1, T = 1] - E[Y|X, I = 1, T = 0]\} \\ -\{E[Y|X, I = 0, T = 1] - E[Y|X, I = 0, T = 0]\} \quad (3)$$

Where: Y is the dependent variable (pesticide use), I = 1 if the farmer is insured and 0 otherwise, T = 1 in 2012 and 0 in 2008.

Under a linear specification, the dependent variable can be formulated in the following way:

$$Y_{it} = \tau + \alpha I_{it} + \gamma T_{it} + \delta I_{it} T_{it} + X_{it}\beta + \varepsilon_{it} \quad (4)$$

Where: t is the time.

Coefficients estimated with equation (4) provide important measures of differences between TG and CG (Zhao et al., 2016):
- τ is the average dependent variable for farmers in the CG in 2008.
- β is the vector of estimated coefficients associated to variables X.
- α is the average difference of the dependent variable in 2008 cross the TG and CG.
- γ is the average change in the dependent variable over time.
- δ is the ATE.
- $(\alpha+\delta)$ can be interpreted as the mean difference between the average dependent variable across TG and CG in 2012.

As shown by Heckman et al. (1998a, 1998b), DID and PSM models can be combined in order to cumulate the advantages and to reduce the drawbacks of the two methods. The PSM allows to select for the relevant CG for each treated observation. Then, the DID allows to eliminate unobservable and confounding time invariant factors that influence all groups together.

4. Results

4.1 Summary statistics

Summary statistics for the control group and the treatment group are provided for each variable and years 2008 and 2012 in Table 2.

Table 2. Descriptive statistics of variables across treatment and control groups before matching

Descriptive statistics underline that farmers present different characteristics among groups. More precisely, farmers specializing in wine-growing who have purchased crop insurance policies are older but have the same standard gross production than farmers who are not insured. The opposite is observed for farmers specializing in field crops: insured farmers are not older when they are insured but their gross production is higher. No difference is noticed among specializations and groups regarding the farmer's education. Finally, insured wine-growers are more likely to located in less-favored areas than non-insured ones while the opposite is noticed for field crop producers.

Considering the intensity of pesticide use, we notice that, while there is not significant difference between the TC and the CG in 2008 and in 2012 for farms specializing in wine-growing, we observe a significant difference for farms specializing in field crops. For farms specializing in wine-growing, the non-significant effect may indicate that the intensity of pesticides is independent from crop insurance purchase. For farms specializing in field crops, this result may indicate a systematic difference between farmers according to their attitude towards crop insurance.

Consequently, standard DID estimators for field crops may be biased and the use of PSM with matching between treated and controlled groups can take into account this specificity. We also have to mention that even for the wine-growing sector, standard DID estimators can be biased because of the heterogeneity of each group. The equality of means may hide the potential heterogeneity of standard deviation and give a misleading impression that these two groups are immediately comparable.

Whatever the orientation considered, the use of PSM with matching lets appreciate the treatment effect on the basis of comparable groups having the same individual (age, level of education) and structural (less-favored area, standard gross production) characteristics.

4.2 PSM estimates

The first step of the PSM procedure consists in estimating each producer's probability to be treated. The propensity to adopt insurance is therefore estimated in a discrete choice framework with a logit model as shown by equation (1). As recalled by Kuethe and Morehart (2012), the estimated coefficients are not the direct objective of the logit model provided that the model fairly predicts insurance purchase.

We then match treated observations to the control group based on the weighted logit propensity scores. Only farmers who have a correspondence among the control and treated groups on the basis of their individual and structural characteristics are considered. The impact of crop insurance on the intensity of pesticide use is measured through the average treatment effect on the treated (ATT), which is calculated according to equation (2).

Many techniques have been developed to perform the matching, Appendix 1 illustrates the matching using a radius method. The comparison between the figures on the left and on the right for each specialization confirm that the matching is effective, i.e. the observations are properly assigned to the CG and TG. Insured and non-insured farms are therefore comparable with respect to their individual and structural characteristics, so that the PSM with matching allows to measure efficiently the impact of crop insurance on the intensity of pesticide use.

Appendix 1. Distribution of propensity scores for the treated and control groups before and after matching with the radius method

Table 3 presents the results obtained using PSM. Contrary to the descriptive statistics presented on Table 2 that are based on the whole sample, we have here a reduced sample which includes only farms that present the same individual and structural characteristics between the treated and control groups. Hence, the effect measured corresponds only to the impact of crop insurance on the intensity of pesticide use.

Table 3. Treatment effects estimates using PSM

All parameters are similar for the ATT whatever the matching method used (nearest neighbor or radius), which indicates the robustness of our results. They indicate that insurance purchase leads to significantly higher pesticide expenses for field crop producers. By contrast, no effect can be reported for wine-growers.

4.3 DID and PSM-DID estimates

Results from the PSM can then be compared to those of the DID and PSM-DID models. The advantage of PSM-DID model is that it takes into account the fact that treated and control groups present some individual and structural specificities. We can then control for unobservable year effects common to both treatment and control groups. The set of estimates from DID and PSM-DID regression is reported in Table 4.

Whatever the farms specialization, we observe that there is a common trend which is the reduction of the intensity of pesticide use. Beside this trajectory, a main difference is observed between farms specializing in field crops and farms specializing in wine-growing.

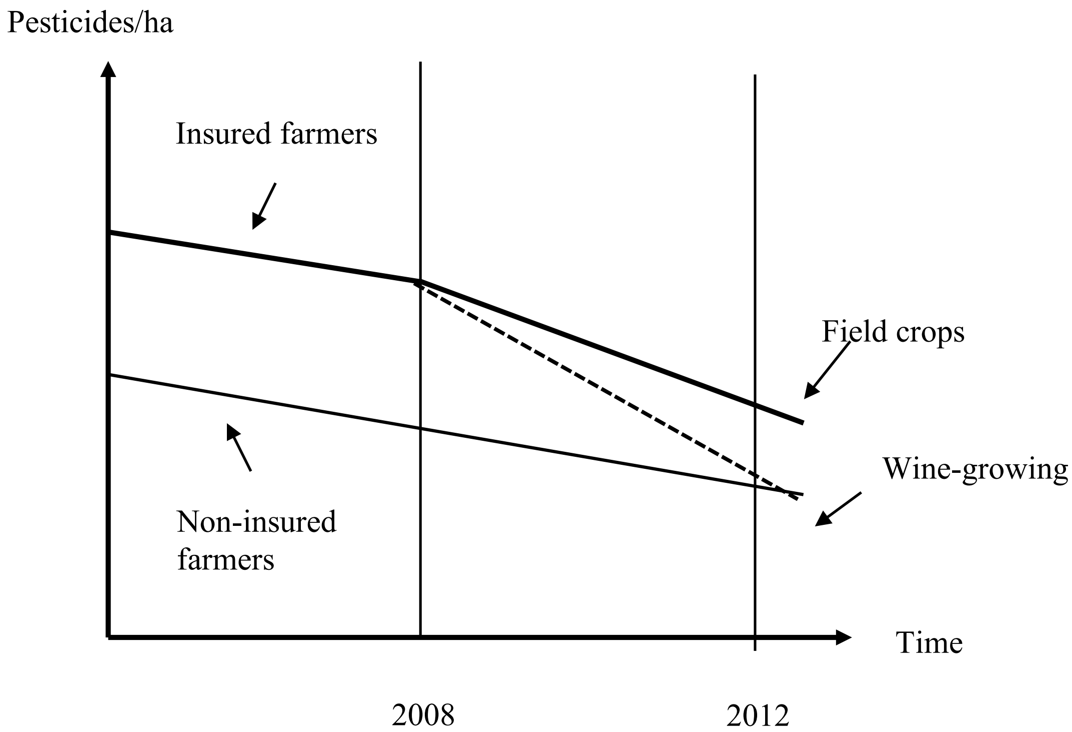
Table 4. Regression results from the DID and PSM-DID models

Farms specializing in field crops exhibit in 2008 the same intensity of pesticide used whatever they belong to treated group or to the control group (parameter α not significant). We have to notice that the reduction of pesticide expenses between 2008 and 2012 (see Table 2) is less important for the treated group (parameter $\alpha+\delta$ significant and positive). This result is valid both for the standard DID and the PSM-DID methods, which confirms the robustness of the results. Given the properties of the estimators, such effects can be attributed to the purchase of crop insurance policies. Because in 2008 the intensity of pesticide use was the same for all farms specializing in field crops, the control group appears to be the most respectful of the environment in 2012.

The evolution observed for farms specializing in wine-growing is quite different according to the PSM-DID model. The first difference is observed in 2008 when the treated group makes a more intensive use of pesticide than the control group (parameter α significant). In 2012, we observe that there is no more difference between these two groups that both exhibit the same intensity of pesticide use (parameter $\alpha+\delta$ not significant). Because all wine-growing farms have reduced their pesticide expenses, the results underline that the treated group has much more reduced its expenses to reach in 2012 the same level than the control group.

Figure 4 summarizes the main results.

Figure 4. Effect of crop insurance on pesticide use between 2008 and 2012



5. Conclusion

For more than a decade, French farmers have been incited to reduce their use of pesticides. In parallel, a modern crop insurance system subsidized by the government has been set up. Both the reduction of pesticide use and the participation to crop insurance are currently questioned for various reasons, especially regarding the changes in risk management practices they imply and their financial consequences. In this context, this study aimed at providing some knowledge about the influence of crop insurance purchase on pesticide use.

In order to measure this effect, the Farm Accountancy Data Network (FADN) was used. This database is representative off all professional French farms and allows to appreciate the individual, structural and financial dimensions of farms. Because the participation to crop insurance is the most important for farm specializing in field crops and wine-growing, our study focused on these two main orientations.

Since crop insurance purchase is not randomly assigned, measuring the impact of this insurance requires to control for the farmers' individual and the farm structural characteristics that lead to such purchase. Different methodologies were adopted, including propensity score matching, difference-in-differences models and a combination of these two methods in order to compare populations of insured and non-insured farmers among them and over time. By controlling individual and structural factors, these methods allowed to stress specifically the role of crop insurance on pesticide use.

The results go hand in hand with the aim of the French government to incite farmers to reduce the use of pesticides and at the same time to purchase crop insurance, these two public policies being clearly distinct. While pesticide expenses are decreasing for field crop and wine-growing producers, insured field crop producers soften this trend while wine-growers amplify it. Such results seem to highlight two different strategies. On the one hand, insured field crop producers seek to maximize their yields, while on the other hand insured wine-growers implement more environmentally-friendly practices by substituting pesticides with insurance.

This study thus emphasized the consequences of crop insurance practices of farmers with respect to their individual profile and that of their farm. Results highlighted that crop insurance seemed to be more efficient in reducing pesticide use for wine-growing than for field crops. Given the observed substitutability of pesticides and insurance for wine-growing, it could be of interest for the French government to couple policies in favor of the development of crop insurance and policies in favor of a decrease of pesticide use. However, some caution would be necessary as the efforts made for the development of crop insurance might also lead to an increase of pesticide use for field crop producers.

Future research should complement this study by examining additional consequences of crop insurance purchase in order to provide in-depth knowledge on the benefits of these policies as well as on its possible drawbacks. Key variables of interest would include the farm net income and indebtedness. The information gained from these analyses would feed into the reflections on the future of the European Common Agricultural Policy regarding risk management.

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Table 1. List and definition of variables

Variable	Unit	Definition
Crop insurance	Dummy	Purchase of a crop insurance policy
Pesticides	€/ha	Pesticides expenses of the farm
Age	Years	Age of the farm holder
Education	Classes	General education of the farm holder
Gross production	€	Gross production of the farm
LFA	Dummy	Farm located in a Less-Favored Area
ETO	Classes	Economic and technical Orientation (field crops and wine-growing)

Table 2. Descriptive statistics of variables across treatment and control groups before matching

	2008					**2012**				
	CG		**TG**			**CG**		**TG**		
Variables	**Mean**	**SD**	**Mean**	**SD**	**t-stat**	**Mean**	**SD**	**Mean**	**SD**	**t-stat**
Field crops										
Pesticides/ha	0.1120	0.0731	0.12854	0.0615	**0.0689***	0.0803	0.0422	0.0977	0.0363	**0.0412****
Age	48.1910	9.4179	48.3254	7.8852	0.9076	52.8115	8.9616	51.4673	8.0348	0.7925
Gross prod.	124,842	85,139	159,374	113,708	**0.0058*****	121,908	93,089	157,684	105,250	**0.0025*****
Wine-growing										
Pesticides/ha	10.3849	17.5484	14.8916	10.1366	**0.0124****	9.3357	9.9480	11.7636	13.1196	0.1362
Age	48.3014	9.6485	44.9318	10.0125	**0.0304****	51.6570	9.2945	49.0869	9.8270	**0.0808****
Gross prod.	237,361	177,264	260,489	235,098	0.4343	242,996	186,700	276,665	299,783	0.2910

		Field crops			**Wine-growing**		
		CG	**TG**	**Total**	**CG**	**TG**	**Total**
Less-Favored Area	**No**	79.06%	91.30%	83.04%	81.56%	67.39%	79.90%
	Yes	20.94%	8.70%	16.96%	18.44%	32.61%	20.10%
	Pearson's chi2	**6.6121*****			**5.0740*****		
General Education	**No**	5.76%	6.52%	6.01%	4.03%	4.35%	4.07%
	Primary	15.18%	21.74%	17.31%	15.85%	13.04%	15.52%
	Secondary	53.93%	44.57%	50.88%	54.18%	50.00%	53.69%
	Higher (short cycle)	22.51%	26.09%	23.67%	22.19%	32.61%	23.41%
	Higher (long cycle)	2.62%	1.09%	2.12%	3.75%	0.00%	3.31%
	Pearson's chi2	3.6921			3.9546		

Source: FADN 2012

Key: *, ** and *** respectively denote significance at the 10%, 5% and 1% levels respectively.

Table 3. Treatment effects estimates using PSM

	Matching method	
	Nearest neighbor	**Radius**
	ATT	**ATT**
	Field crops	
Pesticides/ha	0.0187	0.0165
SE	0.0040	0.0038
t-statistics	4.68	4.35
p-value	0.000***	0.000***
	Wine-growing	
Pesticides/ha	-0.0069	0.0003
SE	0.00465	0.0039
t-statistics	-1.50	0.10
p-value	0.133	0.920

Source: FADN 2008-2012

Key: *, ** and *** respectively denote significance at the 10%, 5% and 1% levels respectively.

Table 4. Regression results from the DID and PSM-DID models

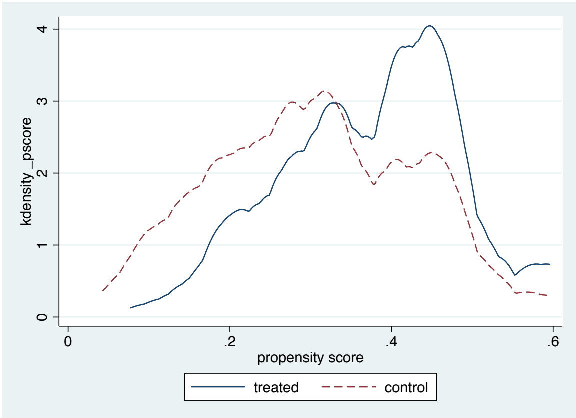
	Standard DID			PSM-DID		
Variables	**α**	**α+δ**	**δ**	**α**	**α+δ**	**δ**
			Field crops			
Pesticides/ha	0.016	0.016	0.001	0.008	0.023	0.015
SE	0.010	0.006	0.012	0.006	0.006	0.009
t-statistics	1.53	2.81	0.04	1.24	3.61	1.68
p-value	0.128	0.005***	0.965	0.216	0.000***	0.093*
			Wine-growing			
Pesticides/ha	-0.001	-0.003	-0.003	0.023	0.000	-0.023
SE	0.014	0.006	0.015	0.009	0.009	0.013
t-statistics	-0.05	0.63	0.18	2.55	0.00	1.82
p-value	0.958	0.529	0.858	0.011**	0.999	0.069*

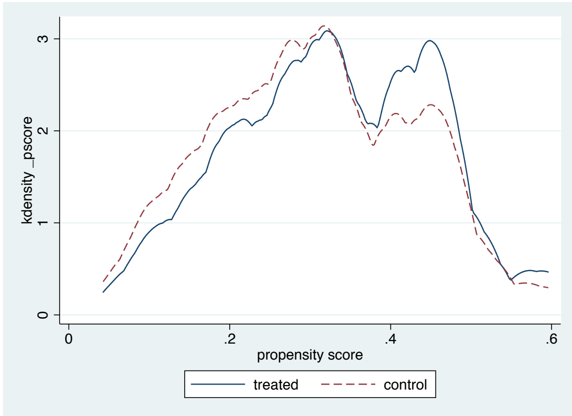
Source: FADN 2008-2012

Key: *, ** and *** respectively denote significance at the 10%, 5% and 1% levels respectively.

Appendix 1. Distribution of propensity scores for the treated and control groups before and after matching with the radius method

Field crops





Wine-growing