How does crop insurance influence pesticide use? Evidence from French farms

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Review of Agricultural, Food and Environmental Studies (2020) 101:461–485
https://doi.org/10.1007/s41130-020-00129-5

RESEARCH ARTICLE

How does crop insurance influence pesticide use? Evidence from French farms

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Received: 21 March 2019 / Accepted: 20 October 2020 / Published online: 9 November 2020

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. To that aim, the paper implements propensity score matching, difference-in-differences models, and a combination of these two methods in order to compare two similar populations of insured and non-insured farmers. Using data from the Farm Accountancy Data Network (FADN), we consider French farms which cultivate field crops and quality wine-growing, the two main productions that participate the most to crop insurance and that use intensively pesticides. 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 has no impact for field crops and quality wine-growing. Meanwhile, the land allocated to each crop within the farm changes. These results question a possible substitutability, for some productions, between crop insurance and pesticides as risk management tools.

Keywords Crop insurance · Pesticides · France · FADN · Field crops · Quality wine-growing

JEL classification G22 · Q12 · Q14

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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 (Coble and Knight 2002). 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 led to an increase in the number and size of farms insured. Two critical steps occurred: in 2005 when crop insurance was generalized to a wide set of crops and hazards (Enjolras and Sentis 2011) and in 2010 when crop insurance was considered by the government as the principal instrument to manage crop yield risks (Decid and Risk 2019). Starting from 2010, French farmers who do not purchase crop insurance cannot receive any public support aimed at compensating losses from the most frequent weather-related hazards.

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). In counterpart, 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 which has been a leading country regarding pesticide expenses in Europe[1] and the 7th largest consumer worldwide[2] over the last decade. Many differences exist among crops: while arable crops represent 48% of chemical input expenditures, they account for only one third of the land farmed (Baschet and Pingault 2009). Wine-growing accounts for 14% of chemical inputs expenditure but represents only 4% of the land farmed. In 2008, the government decided to reduce consumption of chemical inputs by 50% by 2018 within the implementation of Ecophyto I framework (Butault et al. 2010). 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 for both 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.

Many ways to reduce pesticides have been studied in the literature such as changes in agricultural practices (Baschet and Pingault 2009) and taxation (Finger et al. 2017). Among them, crop insurance and pesticides have been

[1] According to Eurostat data, available online: http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=aei_fm_salpest09

[2] According to FAO data, available online: http://www.fao.org/faostat/en/#data/RP/visualize

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). Indeed, both pesticides and crop insurance policies contribute to preserve farm income. One has to note that pesticides and insurance are not explicitly considered potential substitutes because the modalities of use of both products are rather different. 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. Most studies intend to measure instant or annual potential substitution effects between these two risk management strategies. To that aim, they propose models with simultaneous equations or panel data. However, they fail to capture whether insured farms change their productive pattern regarding pesticides over several years. 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 study how the purchase of crop insurance influences in the long run pesticide use at the farm scale in France. To do so, we adopt a methodology which compares populations of insured and non-insured farmers over several years, by controlling for some individual and structural parameters of the farmer and his farm. More specifically, we use difference-in-differences methods and propensity score matching because these methods allow simulating a controlled experiment (Antonakis et al. 2010). They have already 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). Using this method, we propose to test whether crop insurance purchase has or does not have a negative influence on pesticide expenses and to compare the observed trend with non-insured farmers. Our contribution extends that of Roberts et al. (2003) by using propensity score matching techniques and by proposing an application to the French case.

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 FADN sample from 2008 to 2012. Moreover, we focus the analysis on specializations prone to purchase crop insurance and to use intensively pesticides: field crops and quality wine-growing.

The paper is organized as follows. "Literature review on the impacts of crop insurance on pesticide use" provides the conceptual framework which considers the link between crop insurance and pesticide use. "Empirical framework" introduces the empirical modeling, providing full details on the sample characteristics and the econometric models. "Results" presents the results. "Conclusion" offers some concluding remarks.

Literature review on the impacts of crop insurance on pesticide use

The aim of this section is to present the theoretical framework that addresses the link between crop insurance and pesticides. At first, we present these two risk management instruments. Then, we focus on the complex relationship between them.

Two widely used risk management instruments: crop insurance and pesticides

The determinants of farmers' participation in crop insurance scheme have been extensively examined in the literature. In France, Enjolras and Sentis (2011) used data from the Farm Accountancy Data Network (FADN) for years 2003 to 2006. Chakir and Hardelin (2014) conducted a study on farms located in the French 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. 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) revealed 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 USA 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 contrasted results according to the crops considered: they reported a modest reduction of chemical input applications on tobacco and cotton crops and a modest increase on corn.

Pesticides refer to a large set of chemical products that help producers secure and increase yields and profits (Fernandez-Cornejo et al. 1998). Their application is a decision which closely depends on the individual strategy of the producer and of his preferences towards risk (Leathers and Quiggin 1991). For instance, 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 parameters influence pesticide use. Fernandez-Cornejo and Ferraioli (1999) and Wu (1999) showed that educated and younger farmers apply fewer pesticides because they are more aware of their drawbacks. Aubert and Enjolras (2014a) and Mishra et al. (2005) also proved that productive farms and farms located in less-favored areas are more prone to pesticide use. Indeed, such areas face natural handicaps (e.g., lack of water and unfavorable climate) or are mountainous or hilly, which increases production risk.

Crop insurance and pesticide use: a complex relationship

Scholars have long noticed that crop insurance policies share a same goal with pesticide applications: protecting crop yields (Babcock and Blackmer 1994; Hall and Norgaard 1974). For that reason, it has also been suggested that pesticide use and crop insurance purchase might be endogenous, an assumption widely validated by the literature (Babcock and Hennessy 1996; Chakir and Hardelin 2014; 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. Insurance purchase also 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. By contrast, pesticide use is more flexible and applications can be performed when necessary (Aubert and Enjolras 2014b). Nevertheless, the decision to take out crop insurance and to apply pesticides is the farmer's personal choice.

The direction of the causality between insurance purchase and pesticide use leads to a strong debate in the literature, when considering effects at the intensive and at the extensive margins. At the intensive margin, 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; Mishra et al. 2005). Similarly, farmers demonstrating little risk aversion can consider pesticides and insurance as substitutes (Babcock and Hennessy 1996). Because both mechanisms provide a sort of certainty equivalent for farmer, the adoption of crop insurance may result in a progressive decrease of pesticide applications and expenses, at least for some crops (Roberts et al. 2003). However, pesticide applications may increase expected yields 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).

At the extensive margin, insurance purchase may influence land allocation among crops, while bringing marginal land into production. Such effects may have implications in return regarding pesticide use. As shown by Wu (1999) and Finger et al. (2016), crop insurance is likely to increase the riskiness of farm production and thus pesticide applications. By contrast, Mishra et al. (2005) do not find a significant influence of revenue insurance on pesticide use, except in areas with some environmental fragility.

Empirical framework

This section develops the empirical framework to test the implications of purchasing crop insurance policies on pesticide use. After a presentation of the development of crop insurance in France and of the 2010 reform, we present the data used for the analysis. Finally, we detail the estimation methods.

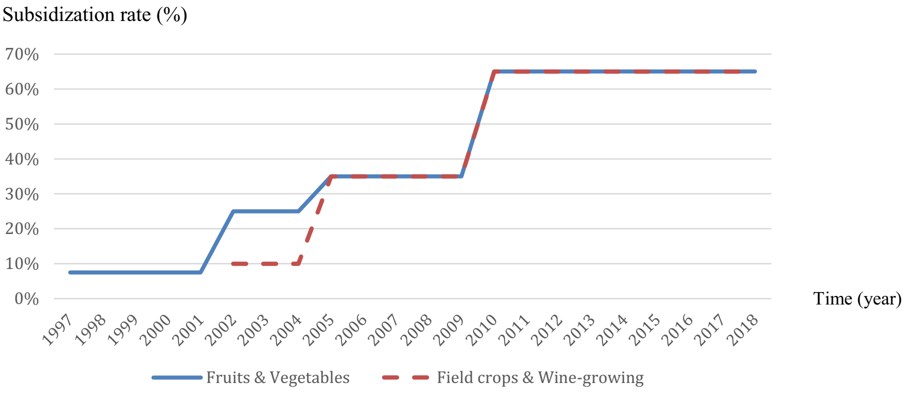
The development of crop insurance policies in France

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. 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 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 to purchase private insurance policies. Because the subsidy compensated the increase in crop insurance premiums due to a better hedging, crop insurance became popular. Two 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 at the same time increased to 65% (Fig. 1).

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



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.

Fig. 1 Evolution of subsidization rates by production. Source: Own representation after data from the French Ministry of Agriculture. 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 subsidizes the remaining 25%. Funds come from the 2nd Pillar of the Common Agricultural Policy, which allows for plurennial planning.

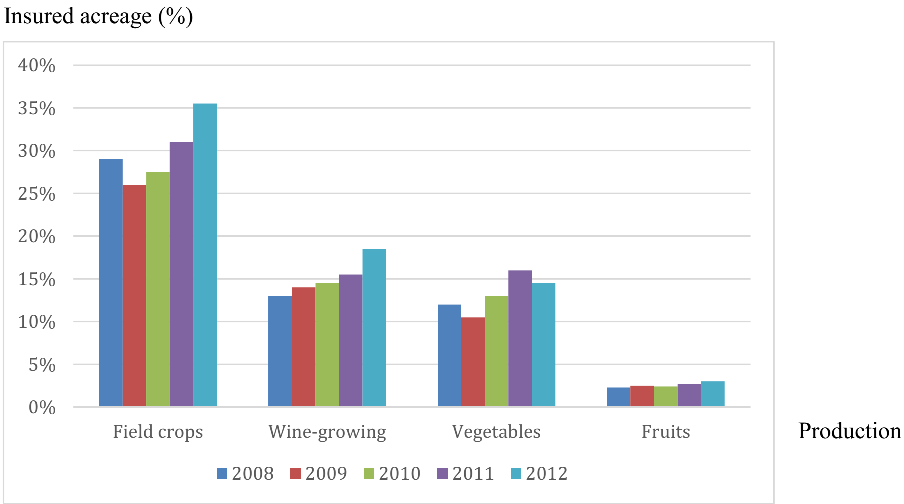
As shown by Fig. 2, the evolution of insured acreage increased overtime. Field crops appear to be the most insured production, followed by wine-growing and vegetables. By contrast, fruits are not correctly insured, which translates in substantial losses for concerned farmers in case of unfavorable weather conditions.

Data

We use a survey of French farmers belonging to the Farm Accountancy Data Network (FADN). This survey offers a reliable way to access individual, structural, and financial characteristics of professional farms, thereby providing useful information about their expenses. On average, 7000 farmers are surveyed each year, accounting for almost 300,000 extrapolated farms. The whole sample is representative of all professional French farms, which reinforces the scope of our results. 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 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 3 years after the introduction of multi-peril crop insurance policies (in 2005) while 2012 is 2 years after the government decided not to hedge any more insurable risks (in 2010). As stated before, the 2010 reform was a particular incentive for farmers to increase their crop insurance.

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 quality wine-growing. Our sample finally included 35,087 extrapolated farms over the 5-year period in question.



Source: French Ministry of Agriculture (2018)

Fig. 2 Evolution of insured acreage by production between 2008 and 2012. Source: French Ministry of Agriculture (2018)

Our dependent variable is related to the environmental practices of farmers, measured through the intensity of pesticide expenses, i.e., the amount of expenses divided by the cultivated area. This choice is motivated by the evolution of the physical dimension of farms between 2008 and 2012, so that considering the nominal value of pesticide expenses could lead to biased results. Alternative measures of pesticide use are also implemented in the literature, such as quantities and treatments (Treatment Frequency Index, TFI). However, they cannot be implemented in our case given the lack of data related to pesticide applications in the FADN database. Moreover, as recalled by Möhring et al. (2019), quantitative measures of pesticide use do not necessarily reflect the environmental risks, and they have to be considered with care.

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).

Methodology

We choose a methodology based on natural experiments (Jones and Rice 2011), which is designed to provide evidence of the influence of crop insurance purchase on pesticide expenses. Instead of considering randomized controlled trials, we observe directly participation to crop insurance in France and its subsequent consequences. The impact of purchasing crop insurance policies can be considered a "treatment" on a group of farms. In order to assess the treatment effect, we identify 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.

For the sake of our analysis, we define farmers who purchased crop insurance in 2012 and who were uninsured in 2009 as the treatment group (TG), while farmers insured neither in 2009 nor in 2012 constitute the control group (CG). There are 3762 farmers in the TG (2088 producing field crops and 1674 specializing in quality wine-growing) and 23,010 farmers in the CG (7417 producing field crops and 15,593 specializing in quality wine-growing).

There are several methodologies for determining the impact of a treatment. The two main methods are difference-in-differences (DID) and propensity score matching (PSM). The DID method compares the TG and CG before and after treatment. The PSM method corrects the treatment effect for any observable characteristics in order to reduce selection bias. It estimates the causal effect of the treatment between the TG and CG, taking into account the difference in the composition of observable characteristics between the two groups. The combination of the two DID and PSM methods is called PSM-DID. This method compares the treated group to the control group, before and after treatment, correcting for any selection bias due to observable characteristics.

Given the number of farms considered in the analysis, the DID method appears preferable to the synthetic control method, which is more adapted to the study of one or of a limited number of units exposed to a program (Kreif et al. 2015). Some papers also propose to substitute or complement PSM with instrumental variables (IV) (Ichimura and Taber 2001; Butry 2005). However, the validity of IV depends largely on assumptions made and requires strong instruments (Leslie and Ghomrawi 2008). In a detailed

Table 1 List and definition of variables

Variable	Unit	Definition
Crop insurance	Dummy	Purchase of a crop insurance policy
Pesticide intensity	€/ha	Pesticides expenses of the farm per hectare
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 (specialization)
Field crop area	Hectare	Total area of field crops
Share of field crop area	%	Share of area dedicated to field crops
Common wheat area	Hectare	Total area of common wheat
Share of common wheat area	%	Share of area dedicated to common wheat
Durum wheat area	Hectare	Total area of durum wheat
Share of durum wheat area	%	Share of area dedicated to durum wheat
Corn area	Hectare	Total area of corn
Share of corn area	%	Share of area dedicated to corn
Barley area	Hectare	Total area of barley
Share of barley area	%	Share of area dedicated to barley
Rapeseed area	Hectare	Total area of rapeseed
Share of rapeseed area	%	Share of area dedicated to rapeseed
Sunflower area	Hectare	Total area of sunflower
Share of sunflower area	%	Share of area dedicated to sunflower
Soybean area	Hectare	Total area of soybean
Share of soybean area	%	Share of area dedicated to soybean
Quality wine-growing area	Hectare	Total area of quality wine-growing
Share of quality wine-growing	%	Share of area dedicated to quality wine-growing
Total area	Hectare	Total cultivated area
Irrigated area	Hectare	Total irrigated area
Share of irrigated area	%	Share of irrigated area
Fodder area	Hectare	Total fodder area
Share of fodder area	%	Share of area dedicated to fodder
Fallow land	Hectare	Total fallow land
Share of fallow land	%	Share of land dedicated to fallow
Herfindahl index	Index	Herfindahl index of crop diversification

analysis, Heckman (1997) argues that for analyses focusing on behavioral models of program participation, instrumental variables are not suitable. Moreover, the results are less sensitive to the model specification with PSM than with IV, thus motivating the use of PSM for the estimation of treatment effects (Butry 2005).

We present these different techniques in more detail below.

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 specifying 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, E is a mathematical expectation, β is the vector of estimated coefficients, I is a dichotomic variable which equals 1 if the farmer is insured in 2012 and 0 otherwise, $i = 1,\ldots,n$ denotes farm observations, and ε is the random error.

$P(X_i)$ is generally estimated through logit models which include observed farmer 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 to a close farmer in the 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, and its location in less-favored areas (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 (gross production 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).[3]

Several methodologies can be used to identify good matches between the TG and the GC. The nearest neighbor method matches observations according to their closest proximity in terms of propensity score. The main risk is a poor match if propensity scores differ too much (Smith and Todd 2005). For this reason, fixing a tolerance threshold increases the quality of the fit but may reduce the number of matched data. The radius matching method considers the size of the local neighborhood around the propensity score (Dehejia and Wahba 2002). It reduces the risk of mismatch and results in oversampling when good matches are available. In order to validate the robustness of the results obtained, both the nearest neighbor and radius matching methods will be considered.

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

$$ATT = E[Y_i(1) - Y_i(0)|T_i = 1] \tag{2}$$

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

where Y is the outcome variable (pesticide use), $Y_i(1)$ the outcome of the treated group and $Y_i(0)$ the outcome of the farmer matching with farmer i in the control group, and E the mathematical expectation.

DID and PSM-DID estimates

The difference-in-differences models basically measure 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.

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

$$\begin{aligned} ATE &= E[Y_i(1) - Y_i(0)] \\ &= \{E[Y|X, I=1, T=1] - E[Y|X, I=0, T=1]\} \\ &\quad - \{E[Y|X, I=1, T=0] - E[Y|X, I=0, T=0]\} \end{aligned} \tag{3}$$

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

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

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

where t is the time.

Coefficients estimated with Eq. (4) provide important measures of differences between TG and CG (Zhao et al. 2016):

- τ is intercept of the model.
- β is the vector of estimated coefficients associated to variables X.
- α is the average difference of the dependent variable in 2008 across 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 the 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 selecting 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.

Results

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.

Considering the intensity of pesticide use, we notice that there is no significant difference between the TC and the CG in 2008 and in 2012 for farms specializing in quality wine-growing. We observe a significant difference for farms specializing in field crops in 2012. For farms specializing in quality 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.

When considering their production and acreage, we notice strong differences between farms according to their specialization. While insured field crop producers do not cultivate a larger area compared to non-insured producers, land allocation is different. At the plot level, they produce less corn but more common wheat and their fallow land is higher. This difference is observed both in 2008 and in 2012. Between these 2 years, the only difference is the decrease of sunflower area of insured farms. Insured quality wine-growing producers also increased their cultivated areas compared to non-insured ones. This extension did not concern vine area but other productions, which may indicate a need for diversification.

Whatever the production considered, farmers present different characteristics among groups. More precisely, farmers who have purchased crop insurance policies are younger (quality wine-growing) and their farms present a higher standard gross production (field crops) compared to farms that are not insured. No difference is noticed among specializations and groups regarding the farmer's education. Finally, while insured field crop producers are less likely to be located in less-favored areas, insured wine-growers are more likely to be located in these areas.

All these differences underline that standard DID estimators for field crops may be biased and the use of PSM with matching between treated and controlled groups is designed to take into account this specificity. We also have to mention that even for quality wine-growing which exhibits little difference between groups, standard DID estimators may be biased because of the heterogeneity of each group. An 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.

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

	2008					2012				
	CG		TG			CG		TG		
Variables	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	***t*-stat**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	***t*-stat**
Field crops										
Pesticide intensity	0.14	0.08	0.13	0.07	*0.80*	0.09	0.04	0.10	0.04	*0.04***
Total area	127.52	67.29	135.35	81.85	*0.52*	121.84	67.92	139.96	86.35	*0.13*
Field crop area	105.91	57.65	112.55	90.61	*0.57*	101.23	60.93	111.21	89.12	*0.38*
Share of field crop area	0.84	0.14	0.82	0.17	*0.45*	0.83	0.15	0.80	0.20	*0.21*
Common wheat	42.02	35.17	56.90	50.61	*0.03***	38.77	34.43	55.18	49.57	*0.01****
Share of common wheat area	0.32	0.19	0.41	0.23	*0.01****	0.30	0.19	0.39	0.24	*0.01****
Durum wheat	8.46	23.15	6.80	27.81	*0.69*	7.87	22.04	4.81	23.84	*0.40*
Share of durum wheat area	0.06	0.15	0.04	0.12	*0.42*	0.06	0.15	0.30	0.12	*0.22*
Corn area	20.57	28.88	12.30	31.82	*0.10**	19.86	23.97	13.48	27.09	*0.11*
Share of corn area	0.21	0.27	0.11	0.24	*0.02***	0.22	0.27	0.12	0.26	*0.03***
Barley area	13.35	17.93	14.10	15.10	*0.80*	11.04	19.81	12.81	18.34	*0.57*
Share of barley area	0.10	0.11	0.11	0.11	*0.51*	0.07	0.10	0.09	0.11	*0.33*
Sunflower area	7.48	12.24	5.25	11.50	*0.33*	8.13	16.02	3.44	9.55	*0.04***
Share of sunflower area	0.06	0.11	0.04	0.08	*0.21*	0.07	0.12	0.03	0.09	*0.03***
Rapeseed area	13.91	16.88	17.05	23.49	*0.33*	15.23	19.23	20.49	27.80	*0.14*
Share of rapeseed area	0.09	0.10	0.11	0.09	*0.33*	0.11	0.11	0.13	0.11	*0.27*
Soybean area	0.13	0.98	0.15	1.06	*0.91*	0.33	2.02	0.98	6.41	*0.30*
Share of soybean area	0.01	0.01	0.01	0.01	*0.71*	0.03	0.22	0.01	0.03	***0.67***
Irrigated area	16.24	37.13	19.00	54.30	*0.71*	15.68	35.82	18.21	47.02	*0.69*
Share of irrigated area	0.14	0.28	0.12	0.26	*0.62*	0.15	0.29	0.13	0.27	*0.71*
Fodder area	6.67	14.28	5.35	16.97	*0.61*	8.67	15.78	8.53	18.55	*0.96*

Table 2 (continued)

Share of fodder area	0.05	0.09	0.03	0.08	*0.24*	0.07	0.12	0.07	0.11	*0.60*
Fallow land	8.11	8.58	12.50	29.43	*0.14*	4.92	6.57	8.53	18.15	*0.05***
Share of fallow land	0.06	0.05	0.07	0.09	*0.49*	0.04	0.05	0.04	0.06	*0.99*
Herfindahl index	0.36	0.17	0.39	0.19	*0.32*	0.36	0.17	0.40	0.20	*0.15*
Age	49.12	9.55	48.68	8.06	*0.78*	53.85	8.87	52.89	7.53	*0.48*
Gross production	113,601.00	64,544.61	135,014	112,613.40	*0.13*	110,343	67,721.80	137,504	107,247.60	*0.03***
Quality wine-growing										
Pesticide intensity	0.06	0.01	0.07	0.01	*0.85*	0.05	0.01	0.05	0.01	*0.33*
Total area	20.38	1.35	22.57	3.19	*0.59*	22.17	1.36	29.69	4.80	*0.08**
Vine area	15.14	0.86	15.85	1.70	*0.78*	13.82	0.83	13.64	1.99	*0.94*
Share of vine area	0.89	0.02	0.86	0.05	*0.53*	0.81	0.02	0.71	0.07	*0.14*
Irrigated area	1.45	0.44	2.06	1.65	*0.67*	2.45	0.59	3.19	1.74	*0.68*
Share of irrigated area	0.04	0.01	0.06	0.04	*0.58*	0.06	0.01	0.06	0.03	*0.92*
Fodder area	0.99	0.35	1.25	0.58	*0.80*	1.18	0.36	1.63	0.69	*0.67*
Share of fodder area	0.03	0.01	0.04	0.02	*0.39*	0.03	0.01	0.04	0.02	*0.52*
Fallow land	1.13	0.48	0.59	0.26	*0.70*	1.34	0.26	2.25	0.79	*0.26*
Share of fallow land	0.03	0.01	0.02	0.01	*0.52*	0.04	0.01	0.05	0.02	*0.59*
Herfindahl index	0.94	0.03	0.88	0 .09	*0.56*	0.90	0.03	0.81	0.08	*0.31*
Age	48.17	0.58	43.74	1.79	*0.01****	51.63	0.52	48.88	1.58	*0.08**
Gross production	250,984.50	10,596.74	263,180.40	44,378.67	*0.72*	242,734.60	10,256.08	274,374.20	50,240.16	*0.36*

		Field crops			Quality wine-growing		
		CG	**TG**	**All**	**CG**	**TG**	**All**
Less-favored area	**No**	74.22	87.50	78.26	81.23	62.50	79.18
	Yes	25.78	12.50	21.74	18.77	37.50	20.82
	Pearson's χ^2	*0.044***			*0.006****		

Table 2 (continued)

General education	**No**	7.03	3.57	5.98	3.38	4.98	3.56
	Primary	17.19	25.00	19.57	14.77	15.01	14.79
	Secondary	53.91	48.21	52.17	54.77	44.99	53.70
	Higher	21.87	23.22	22.28	27.07	35.00	27.95
	Pearson's χ^2	*0.669*			*0.364*		

Source: FADN 2008–2012. *, **, and *** respectively denote significance at the 10%, 5%, and 1% levels. *CG* denotes the control group while *TG* denotes the treated group

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 Eq. (1). This model is primarily designed to predict the probability of purchasing crop insurance, not to estimate coefficients (Kuethe and Morehart 2012).

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 Eq. (2).

Many techniques have been developed to perform the matching; Appendix Fig. 4 illustrates the matching using a radius method. The comparison between the figures on the left and on the right for each specialization confirms 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 measuring efficiently the impact of crop insurance on the intensity of pesticide use.

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.

We first notice that almost all parameters are similar for the ATT whatever the matching method used (neighbor or radius), which indicates the robustness of our results. They indicate that insurance purchase does not influence the intensity of pesticide used, whatever the production considered.

When considering farm structure and acreage, we notice strong differences among productions. It seems that insured field crop producers adopt a less risky behavior. While the total area and the pesticide intensity are stable over the period, farmers increase their share of common wheat and corn areas as well as fallow land while reducing their share of irrigated, corn, and sunflower areas. This reorganization of productions is coupled with an increase of the Herfindahl index that reveals a higher diversification of productions implemented.

Although these effects are contrasted according to the matching method (neighbor or radius), it seems that wine-growers reduce the land allocated to wine production while they increase their total area. Insured wine-growers increase their irrigated area and they reduce their fodder area. While wine-growers reallocate the land they cultivate, they maintain the same degree of diversification.

DID and PSM-DID estimates

The advantage of the 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

Table 3 Treatment effect estimates using PSM

	Field crops		Quality wine-growing	
Matching method	Neighbor	Radius	Neighbor	Radius
Pesticide intensity	0.007	0.007	0.008	0.001
Total area	7.686	3.340	0.847	5.224**
Considered crop area	6.758	− 0.195	− 2.997***	0.365
Share of the considered crop area	− 0.016	− 0.033**	0.020	− 0.057*
Common wheat	13.486***	9.356***		
Share of common wheat area	0.095***	0.071***		
Durum wheat	− 0.703	− 1.001		
Share of durum wheat area	− 0.006	− 0.009		
Corn area	− 8.896***	− 3.092***		
Share of corn area	− 0.111***	− 0.095***		
Barley area	− 0.645	− 0.688		
Share of barley area	− 0.001	0.004		
Sunflower area	− 1.074	− 2.740***		
Share of sunflower area	− 0.012*	− 0.018**		
Rapeseed area	4.336**	2.756		
Share of rapeseed area	0.017**	0.012		
Soybean area	0.254	0.216		
Share of soybean area	0.002	0.001		
Irrigated area	0.840	2.551	2.725***	1.739*
Share of irrigated area	− 0.052**	− 0.019	0.039**	0.013
Fodder area	− 0.098	0.189	− 2.566***	− 2.890***
Share of fodder area	− 0.002	0.003	− 0.048***	− 0.037***
Fallow land	2.802*	2.977*	0.437	0.511
Share of fallow land	− 0.004	− 0.001	− 0.006	− 0.003
Herfindahl index	0.025*	0.037**	0.054	− 0.066
Number of observations	506	844	378	1712

Source: FADN 2008–2012

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

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 farm specialization, we observe a common trend which is the stabilization of the intensity of pesticide use. All of them exhibit in 2008 and in 2012 the same intensity of pesticide used whatever they belong to treated group or to the control group (parameter α not significant, which is consistent with the descriptive statistics). This result is valid for both the standard DID and the PSM-DID methods, which confirms the robustness of this result.

Besides this common trajectory, the results underline a reduction of the share of the area dedicated to the main specialization (field crops or quality wine-growing). Insured

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

		Field crops		Quality wine-growing	
		DID	PSM-DID	DID	PSM-DID
Pesticide intensity	α	−0.003	−0.002	0.003	0.003
	$\alpha+\delta$	0.013	0.010	−0.007	−0.003
	δ	0.017	0.013	−0.010	−0.006
Total area	α	7.828	5.791	2.190	1.771
	$\alpha+\delta$	18.119	7.620	7.518*	9.068***
	δ	10.291	1.829	5.328	7.296**
Considered crop area	α	6.637	4.005	0.708	5.000
	$\alpha+\delta$	9.975	−0.755	−0.186	0.000
	δ	3.338	−4.760	−0.894	−5.000
Share of the considered crop area	α	−0.019	−0.032	−0.036	0.000
	$\alpha+\delta$	−0.034	−0.059**	−0.097	−0.200***
	δ	−0.015	−0.027	−0.061	−0.200**
Common wheat	α	14.878**	12.454*		
	$\alpha+\delta$	16.409**	9.740		
	δ	1.531	−2.714		
Share of common wheat area	α	0.092***	0.081**		
	$\alpha+\delta$	0.088***	0.053		
	δ	−0.004	−0.028		
Durum wheat	α	−1.657	0.029		
	$\alpha+\delta$	−3.050	−2.361		
	δ	−1.393	−2.390		
Share of durum wheat area	α	−0.019	−0.007		
	$\alpha+\delta$	−0.028	−0.013		
	δ	−0.009	−0.006		
Corn area	α	−8.265*	−9.182**		
	$\alpha+\delta$	−6.381	−6.373		
	δ	1.998	2.808		
Share of corn area	α	−0.099**	−0.111***		
	$\alpha+\delta$	−0.095**	−0.089**		
	δ	0.005	0.022		
Barley area	α	0.752	−0.796		
	$\alpha+\delta$	1.777	−1.684		
	δ	1.025	−0.888		
Share of barley area	α	0.012	0.005		
	$\alpha+\delta$	0.016	−0.002		
	δ	0.004	−0.007		
Sunflower area	α	−2.228	−1.114		
	$\alpha+\delta$	−4.688**	−3.718*		
	δ	−2.459	−2.604		
Share of sunflower area	α	−0.021	−0.013		

Table 4 (continued)

		Field crops		Quality wine-growing	
		DID	PSM-DID	DID	PSM-DID
	$\alpha+\delta$	− 0.037**	− 0.025*		
	δ	− 0.016	− 0.012		
Rapeseed area	α	3.137	2.498		
	$\alpha+\delta$	5.257	2.745		
	δ	2.120	0.248		
Share of rapeseed area	α	0.016	0.012		
	$\alpha+\delta$	0.020	0.013		
	δ	0.004	0.02		
Soybean area	α	0.020	0.115		
	$\alpha+\delta$	0.650	0.896		
	δ	0.631	0.781		
Share of soybean area	α	0.001	0.002		
	$\alpha+\delta$	0.002	0.004		
	δ	0.001	0.002		
Irrigated area	α	2.761	1.877	0.604	0.990
	$\alpha+\delta$	2.531	1.054	0.741	1.807*
	δ	− 0.230	− 0.823	0.137	0.817
Share of irrigated area	α	− 0.024	− 0.030	0.019	0.025
	$\alpha+\delta$	− 0.017	− 0.026	− 0.003	0.017
	δ	0.007	0.004	− 0.022	− 0.008
Fodder area	α	− 1.324	− 1/328	0.257	− 0.129
	$\alpha+\delta$	− 0.145	2.094	0.448	0.128
	δ	1.179	3.422	0.191	0.258
Share of fodder area	α	− 0.017	− 0.016	0.018	0.008
	$\alpha+\delta$	− 0.010	0.013	0.012	0.002
	δ	0.008	0.029	− 0.005	− 0.006
Fallow land	α	4.391*	5.231*	− 0.544	− 0.088
	$\alpha+\delta$	3.605	2.920	0.912	1.633***
	δ	− 0.786	− 2.311	1.456	1.721***
Share of fallow land	α	0.07	0.016*	− 0.011	− 0.002
	$\alpha+\delta$	0.000	0.001	0.010	0.030***
	δ	− 0.007	− 0.015	0.021	0.032**
Herfindahl index	α	0.030	0.020	− 0.058	− 0.000
	$\alpha+\delta$	0.042	0.028	− 0.092	− 0.306***
	δ	0.012	0.008	− 0.034	− 0.306***
Number of observations		349	321	686	645

Source: FADN 2008–2012

*, **, and *** respectively denote significance at the 10%, 5%, and 1% levels. α is the average difference of the dependent variable in 2008 across the treatment group (TG) and the control group (CG), δ is the average treatment effect (ATE), and $(\alpha+\delta)$ can be interpreted as the mean difference between the average dependent variable across TG and CG in 2012

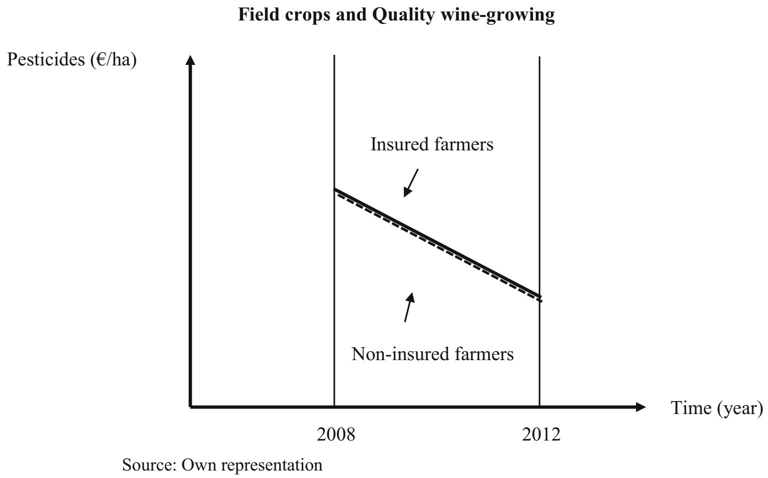


Fig. 3 Effect of crop insurance on pesticide use between 2008 and 2012. Field crops and quality wine-growing

farms diversify their productive strategy by reallocating their land. This strategy is defined in a context where field crop producers stabilize the total area of farm, while wine-growers increase it. In detail, the results reveal that field crop producers reduce the area dedicated to corn and sunflower, while the area dedicated to fallow land increases. For quality wine-growing farms, the reduction of area dedicated to vines is outweighed by the increase of both irrigated and fallow areas. More than a single reallocation of land, wine-growers increase the diversification of their production.

Figure 3 summarizes the main results.

Tu sum up, these results confirm that crop insurance purchase has no specific effect on pesticide use for field crops and quality wine-growing in the medium term. However, crop insurance translates into changes in acreage associated to a reallocation of land inside the farm. Contrary to what Wu (1999) shows, changes in land allocation do not induce any increase in pesticide use.

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, by considering changes in the medium term.

In order to measure this effect, the Farm Accountancy Data Network (FADN) was used. This database is representative of all professional French farms and allows appreciating the individual, structural, and financial dimensions of farms. Because the participation to crop insurance is the most important for farms specializing in field crops and quality wine-growing, our study focused on these two main orientations. We also considered an analysis between years 2008 and 2012. This choice was motivated by a major change in the crop insurance system. Starting from 2010, French farmers who do not purchase crop insurance cannot receive any public support aimed at compensating losses from the most frequent weather-related hazards.

Because crop insurance purchase is not randomly assigned, measuring the impact of this insurance requires controlling 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 stressing specifically the role of crop insurance on pesticide use at the intensive margin. We also considered implications of crop insurance at the extensive margin by considering changes in acreage.

Estimations show that while pesticide use decreases for all crops, the purchase of crop insurance policies has no specific impact for field crops and quality wine-growing. Meanwhile, the land allocated to each crop within the farm changes, without affecting pesticide expenses. These results question a possible substitutability, for some productions, between crop insurance and pesticides as risk management tools. By contrast with most of previous studies, the specificity of our analysis is to consider the implications of crop insurance in the medium run and not over a single year. The results are therefore more meaningful about the implications of crop insurance on risk management.

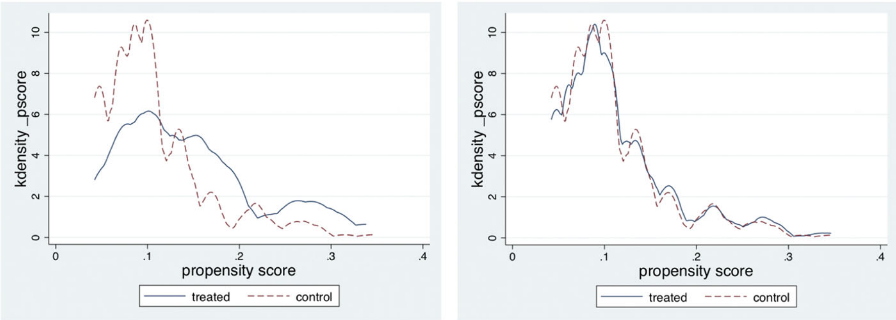
Future research should complement this study by examining additional consequences of crop insurance purchase in order to provide in-depth knowledge on the benefits of these policies as well as on its possible drawbacks. Key variables of interest would include the farm net income and indebtedness. Moreover,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

Compliance with ethical standards

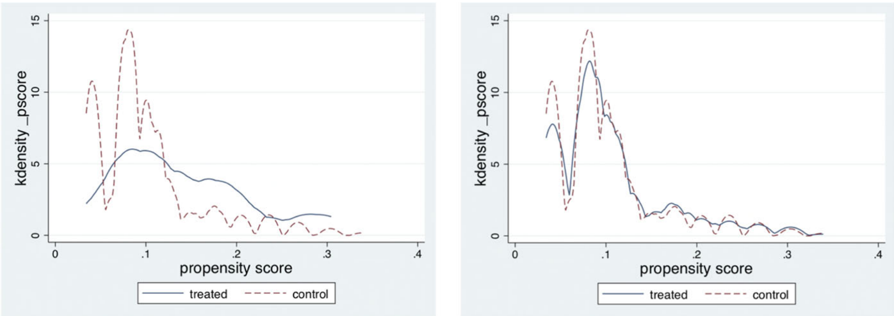
Conflict of interest The authors declare that there is no conflict of interest.

Appendix

Field crops



Quality wine-growing



Source: Own representation

Fig. 4 Distribution of propensity scores for the treated and control groups before and after matching with the radius method. Source: Own representation

References

Antle, J. M., Cole, D. C., & Crissman, C. C. (1998). Further evidence on pesticides, productivity and farmer health: potato production in Ecuador. *Agricultural Economics, 18*, 199–207.

Antonakis, J., Bendahan, S., Jacquart, P., & Lalive, R. (2010). On making causal claims: a review and recommendations. *The Leadership Quarterly, 21*(6), 1086–1120.

Aubert, M., & Enjolras, G. (2014a). The determinants of chemical input use in agriculture: a dynamic analysis of the wine grape-growing sector in France. *Journal of Wine Economics, 9*(1), 75–99.

Aubert, M., & Enjolras, G. (2014b). Between the approved and the actual dose: a diagnosis of pesticide overdosing in French vineyards. *Review of Agricultural and Environmental Studies, 95*(3), 327–350.

Babcock, B. A., & Blackmer, A. M. (1994). The ex post relationship between growing conditions and optimal fertilizer levels. *Review of Agricultural Economics, 16*, 353–362.

Babcock, B. A., & Hennessy, D. A. (1996). Input demand under yield and revenue insurance. *American Journal of Agricultural Economics, 78*, 416–427.

Bardají, I., Garrido, A., Blanco, I., Felis, A., Sumpsi, J.-M., García-Azcárate, T., Enjolras, G., & Capitanio, F. (2016). *State of play of risk management tools implemented by member states during the period 2014–2020: national and European frameworks*. Brussels: European Parliament.

Baschet, J.-F., & Pingault, N. (2009). Reducing pesticides use: the Ecophyto 2018 plan - the role of usage indicators in evaluating the achievement of targets. French Ministry of Agriculture and Fisheries, Statistics and Prospective Service, 4/2009.

Becker, S. O., & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal, 2*(4), 358–377.

Bielza, M., Conte, C., Gallego, F.J., Stroblmair, J., Catenaro, R., & Dittman, C. (2009). Risk management and agricultural insurance schemes in Europe. JRC Reference Reports EUR 23843 EN, JRC 51982.

Böcker, T. G., & Finger, R. (2017). A meta-analysis on the elasticity of demand for pesticides. *Journal of Agricultural Economics, 68*, 518–533.

Butault, J. P., Dedryver, C. A., Gary, C., Guichard, L., Jacquet, F., & Meynard, J. M. (2010). Ecophyto R&D. In *Quelles voies pour réduire l'usage des pesticides? Synthèse du rapport d'étude*. France: INRA.

Butry, D.T. (2005). Estimating the efficacy of fighting fire: propensity score and instrumental variable methods. Paper presented at the North Carolina State University Agricultural Economics Workshop, Raleigh, NC, October 2005.

Chakir, R., & Hardelin, J. (2014). Crop insurance and pesticide use in French agriculture: an empirical analysis. *Revue d'Études en Agriculture et Environnement, 95*(1), 25–50.

Coble, K. H., & Knight, T. O. (2002). Crop insurance as a tool for price and yield risk management. In R. E. Just & R. D. Pope (Eds.), *A comprehensive assessment of the role of risk in U.S. Agriculture* (pp. 445–468). Boston: Kluwer Academic Publisher.

Cornaggia, J. (2013). Does risk management matter? Evidence from the US agricultural industry. *Journal of Financial Economics, 109*(2), 419–440.

Craven, C., & Hoy, S. (2005). Pesticides persistence and bound residues in soil—regulatory significance. *Environmental Pollution, 133*, 5–9.

Decid & Risk (2019). Évaluation du Programme national de gestion des risques et d'assistance technique (PNGRAT), et en particulier de l'assurance récolte, Report for the French Ministry of Agriculture, available online : https://agriculture.gouv.fr/la-gestion-des-risques-en-agriculture

Dehejia, R., & Wahba, S. (2002). Propensity score matching methods for non- experimental causal studies. *Review of Economics and Statistics, 84*(1), 151–161.

Deryugina, T., & Konar, M. (2017). Impacts of crop insurance on water withdrawals for irrigation. *Advances in Water Resources, 110*, 437–444.

Enjolras, G., & Sentis, P. (2011). Crop insurance policies and purchases in France. *Agricultural Economics, 42*(4), 475–486.

Feinerman, E., Herriges, J. A., & Holtkamp, D. (1992). Crop insurance as a mechanism for reducing pesticide usage: a representative farm analysis. *Applied Economic Perspectives and Policy, 14*(2), 169–186.

Fernandez-Cornejo, J., & Ferraioli, J. (1999). The environmental effects of adopting IPM techniques: the case of peach producers. *Journal of Agricultural and Applied Economics, 31*(3), 551–564.

Fernandez-Cornejo, J., Jans, S., & Smith, M. (1998). Issues in the economics of pesticide use in agriculture: a review of the empirical evidence. *Review of Agricultural Economics, 20*(2), 462–488.

Finger, R., & Lehmann, N. (2012). The influence of direct payments on farmers' hail insurance decisions. *Agricultural Economics, 43*(3), 343–354.

Finger, R., Möhring, N., Dalhaus, T., & Enjolras, G. (2016). The effects of crop insurance on pesticide use. Paper presented at the 156th Seminar of the European Association of Agricultural Economists, Wageningen, The Netherlands.

Finger, R., Möhring, N., Dalhaus, T., & Böcker, T. (2017). Revisiting pesticide taxation schemes. *Ecological Economics, 134*, 263–266.

French Ministry of Agriculture (2018). France - Programme national de gestion des risques et assistance technique (PNGRAT). Available online: https://agriculture.gouv.fr/la-gestion-des-risques-en-agriculture

Goodwin, B. K., Vandeveer, M. L., & Deal, J. L. (2004). An empirical analysis of acreage effects of participation in the federal crop insurance program. *American Journal of Agricultural Economics, 86*(4), 1058–1077.

Hall, D. C., & Norgaard, R. B. (1974). On the timing and application of pesticides: rejoinder. *American Journal of Agricultural Economics, 56*(3), 644–645.

Heckman, J. J. (1997). Instrumental variables - response to Angrist and Imbens. *The Journal of Human Resources, 4*, 828–837.

Heckman, J. J., Ichimura, H., & Todd, P. (1998a). Matching as an econometric evaluation estimator. *The Review of Economic Studies, 65*(2), 261–294.

Heckman, J. J., Ichimura, H., Smith, J., & Todd, P. (1998b). Characterizing selection bias using experimental data. *Econometrica, 66*(5), 1017–1098.
Horowitz, J. K., & Lichtenberg, E. (1993). Insurance, moral hazard, and chemical use in agriculture. *American Journal of Agricultural Economics, 75*(4), 926–935.
Horowitz, J. K., & Lichtenberg, E. (1994). Risk-reducing and risk-increasing effects of pesticides. *Journal of Agricultural Economics, 45*(1), 82–89.
Ichimura, H., & Taber, C. (2001). Propensity-score matching with instrumental variables. *The American Economic Review, 91*(2), 119–124.
Ifft, J. E., Wu, S., & Kuethe, T. (2014). The impact of pasture insurance on farmland values. *Agricultural and Resource Economics Review, 43*(3), 390–405.
Ifft, J. E., Kuethe, T., & Morehart, M. (2015). Does federal crop insurance lead to higher farm debt use? Evidence from the Agricultural Resource Management Survey (ARMS). *Agricultural Finance Review, 75*(3), 349–367.
Jones, A. M., & Rice, N. (2011). Econometric evaluation of health policies. In S. Glied & P. Smith (Eds.), *The Oxford handbook of health economics*. Oxford: Oxford University Press.
Just, R. E., Calvin, L., & Quiggin, J. (1999). Adverse selection in crop insurance: actuarial and asymmetric information incentives. *American Journal of Agricultural Economics, 81*, 834–849.
Kott, P.S. (1998). Using the delete-a-group jackknife variance estimator in NASS surveys. NASS Research Report 98–01.
Kreif, N., Grieve, R., Hangartner, D., Turner, A. J., Nikolova, S., & Sutton, M. (2015). Examination of the synthetic control method for evaluating health policies with multiple treated units. *Health Economics, 25*(12), 1514–1528.
Kuethe, T. H., & Morehart, M. (2012). The profit impacts of risk management tool adoption. *Agricultural Finance Review, 72*(1), 104–116.
Leathers, H. D., & Quiggin, J. C. (1991). Interactions between agricultural and resource policy: the importance of attitudes toward risk. *American Journal of Agricultural Economics, 73*(3), 757–764.
Leslie R., & Ghomrawi, H. (2008). The use of propensity scores and instrumental variable methods to adjust for treatment selection bias. SAS Global Forum: Statistics and Data Analysis.
Mishra, A. K., Nimon, R. W., & El-Osta, H. S. (2005). Is moral hazard good for the environment? Revenue insurance and chemical input use. *Journal of Environmental Management, 74*, 11–20.
Möhring, N., Gaba, S., & Finger, & R. (2019). Quantity based indicators fail to identify extreme pesticide risks. *Science of the Total Environment, 646*, 503–523.
O'Donoghue, E.J., Key, N., & Roberts, M.J. (2005). Does risk matter for farm business? The effects of crop insurance on production and diversification, Proceedings of the Annual Meeting of the AAEA, Providence, RI, 24–37 July 2005.
Pan, J., Plant, J. A., Voulvoulis, N., Oates, C. J., & Ihlenfeld, C. (2010). Cadmium levels in Europe: implications for human health. *Environmental Geochemistry and Health, 32*(1), 1–12.
Pannell, D. J. (1991). Pests and pesticides, risk and risk aversion. *Agricultural Economics, 5*, 361–383.
Phimister, E., Roberts, D., & Gilbert, A. (2004). The dynamics of farm incomes: panel data analysis using the Farm Accounts Survey. *Journal of Agricultural Economics, 55*(2), 197–220.
Roberts, M.J., O'Donoghue, E.J., & Key, N. (2003). Chemical and fertilizer applications in response to crop insurance: evidence from Census Micro Data, Proceedings of the Annual Meeting of the AAEA, Montréal, Quebec, 27–30 July 2003.
Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55.
Santeramo, F. G., Adinolfi, F., Capitanio, F., & Goodwin, B. K. (2016). Farmer participation, entry and exit decisions in the Italian crop insurance program. *Journal of Agricultural Economics, 67*(3), 639–657.
Smith, V. H., & Goodwin, B. K. (1996). Crop insurance, moral hazard, and agricultural chemical use. *American Journal of Agricultural Economics, 78*, 428–438.
Smith, J., & Todd, P. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics, 125*(1–2), 305–353.
Uzea, N., Poon, K., Sparling, D., & Weersink, A. (2014). Farm support payments and risk balancing: implications for financial riskiness of Canadian farms. *Canadian Journal of Agricultural Economics/ Revue canadienne d'agroéconomie, 62*, 595–618.
Westhoek, H., Van Zeijts, H., Witmer, M., Van den Berg, M., Overmars, K., Van der Esch, S., & Van der Bilt, W. (2014). *Greening the CAP. An analysis of the effects of the European Commission's proposals for the Common Agricultural Policy 2014–2020*. Hague: Netherlands Environmental Assessment Agency.
Wu, J. (1999). Crop insurance, acreage decisions, and nonpoint-source pollution. *American Journal of Agricultural Economics, 81*(2), 305–320.

Yu, J., Smith, A., & Daniel, A. S. (2017). Effects of crop insurance premium subsidies on crop acreage. *American Journal of Agricultural Economics, 100*(1), 91–114.

Zhao, Y., Chai, Z., Delgado, M. S., & Preckel, P. V. (2016). An empirical analysis of the effect of crop insurance on farmers' income: results from inner Mongolia in China. *China Agricultural Economic Review, 8*(2), 299–313.