# Strategic free-riding for pest control in organic-conventional mixed landscapes

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**Abstract**

Organic and conventional farmers face the same pests but have different technologies and economic incentives to control them. We first theoretically characterize the strategic interactions for pest control between these two types of farmers in mixed landscapes. Our non-cooperative game analysis suggests that a farmer type should strategically free-ride on the other's pest control effort when managing a small enough share of the landscape. The extent of free-riding increases for lower pest exposure, higher relative treatment costs, and lower treatment efficacy. Second, using exhaustive postcode-level French data on insecticide purchases against the vector of an infectious vine disease (*Flavescence dorée*), we provide empirical support for all our theoretical propositions. Our preferred estimates indicate that organic farmers free-ride on conventional farmers' efforts until they represent about 9% of the landscape. After this threshold, organic treatments only partially substitute for conventional treatment reductions, up to a point where conventional farmers could eventually free-ride if the organic landscape share is large enough. The extent of free-riding strongly depends on pest pressure, both farmers never free-riding when pest pressure is high. Differences in relative treatment costs and treatment efficacy also affect free-riding according to model's propositions, but to a lesser extent.

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**JEL Codes**: C57; H41; Q57; R14

# 1 Introduction

Pests and diseases plagued agriculture until the adoption of synthetic pesticides in the 1950s, which greatly enhanced agricultural productivity (Popp et al., 2013), but generated lasting environmental and health damage (Beketov et al., 2013; Dias et al., 2023; Frank, 2024). Organic farming is expected to reduce such damage by prohibiting synthetic pesticides and adopting more environmentally-friendly pest control techniques (Moschitz et al., 2021). However, these techniques are generally less effective than synthetic pesticides (Baker et al., 2020). In the presence of mobile public bads like pests, less effective control from organic farmers could increase pest exposure for all farmers, ultimately prompting conventional farmers to use more synthetic pesticides. This may become a major concern as organic farming, though currently occupying a smaller area, is expanding worldwide (Willer and Lernoud, 2017).

Strategic interactions in pest control have been extensively studied in the theoretical literature on the private control of mobile public bads (e.g., Fenichel et al., 2014; Liu and Sims, 2016; Costello et al., 2017; Tsao and Costello, 2024), highlighting how differences among farmers can influence strategic pest control decisions. As organic and conventional farmers face the same pests but differ in covered landscape shares, treatment efficacy and economic incentives to treat (yields, prices, and costs), this literature suggests that strategic interactions in mixed organic-conventional landscapes would be complex. Yet, existing theoretical results do not provide clear propositions on how these factors jointly shape strategic behaviours. Empirical assessments, which could help to understand these interactions, are also quite uncommon in the literature (existing empirical studies mostly measure the efficacy of pest control strategies without strategic interaction; e.g., Lazarus and Dixon, 1984; Gramig and Wolf, 2007; Chambers and Tzouvelekas, 2013; Jardine and Sanchirico, 2018). Recently, Larsen et al. (2024) found that organic farmers located in landscapes with higher organic shares used insecticides less, whereas conventional farmers surrounded by organic agriculture used them more. While these estimates suggest the potential presence of strategic interactions for pest control between farmers in mixed organic-conventional landscapes, a comprehensive integrated empirical-theoretical assessment is still needed to better understand these interactions.

Our paper addresses this issue. We develop a static non-cooperative game theory model with two representative farmers – one organic and one conventional – sharing exposure to the same mobile public bad, but differing in terms of (i) covered landscape shares, (ii) economic incentives to protect their crops (i.e., treatment costs relative to agricultural revenues), and (iii) crop control technologies (i.e., authorized pesticides). We derive theoretical propositions about the effects of these differences on optimal pest control strategies, identifying *when* and *under what conditions* each farmer should free-ride on the other's efforts by no longer controlling pests. We then empirically assess these propositions by exploiting cross-sectional differences from exhaustive postcode-level French data separately reporting on conventional and organic insecticide purchases for the particular case of *Flavescence dorée* (FD), a widespread, vineyard-specific disease transmitted by the invasive leafhopper *Scaphoideus titanus* (Malembic-Maher et al., 2020; Tramontini et al., 2020).

The real-world characteristics of FD make it well-suited to an empirical evaluation of the theory. First, since FD only affects vines and *Scaphoideus titanus* feeds exclusively on vine plants (Tramontini et al., 2020), we can focus on the control of this specific disease among the particularly homogeneous population of French winegrowers (who presumably differ only in their economic incentives and pest control technology). Second, conventional and organic farmers face the same contamination risk but leafhoppers can only be organically controlled by one insecticide: *pyrevert©*. Because this insecticide is not used for other insects *within* or *outside* vineyards, its purchase data reliably indicate the extent of organic treatments.[1] Third, France delineates mandatory control perimeters (MCPs) around FD contamination clusters (Ay and Gozlan, 2020),[2] providing information about the geographical distribution of FD pressure. Fourth, since organic wines have a higher value than conventional wines (Corsi and Strøm, 2013), the death of FD-infected vines within a few years leads to greater damage for organic than conventional farmers. Fifth, the efficacy of organic and conventional farmers' FD control technologies are objectively different, *pyrevert* being leached out by the slightest rainfall event (contrary to more persistent conventional insecticides).

Our empirical results support all our theoretical propositions. Specifically, our primary propositions suggest that, *ceteris paribus*, organic farmers should strategically free-ride on conventional farmers' efforts if their covered landscape share is below a threshold determined analytically by the model. Our preferred estimates show that the average organic farmer free-rides when organic farming covers less than 9% of the landscape (i.e., in about 75% of French postcodes). Above this threshold, organic farmers should theoretically increase their treatment efforts as their landscape share grows, while conventional farmers should reduce theirs (albeit not necessarily symmetrically). This substitution pattern is indeed only *partial*, organic treatments replacing about 70% of conventional treatment reductions empirically. Then, theory predicts that the average conventional

[1] By comparison, there are 108 *conventional* insecticides approved against FD, some of which can also be used against other insects and on other crops. The measurement errors from alternative uses of conventional insecticides are discussed in Section 3. Note also that this leafhopper has no known predators in France, preventing the implementation of any biological control in the context of FD management.

[2] In place since 2013, MCPs are revised each year to include contaminated areas as well as all adjacent municipalities with vineyards, typically covering an area of about 4 km $\times$ 4 km (roughly 20% of a typical French postcode).

farmer should free-ride when the organic landscape share exceeds a threshold, which does occur in our data when conventional farming occupies less than 44% of the landscape. Because such landscapes are rare (only 3% of French postcodes are dominated by organic vineyards), this latter threshold is imprecisely estimated. Yet, our theory can explain this asymmetry in the free-riding pattern: organic farmers are expected to free-ride for a smaller range of landscape shares than conventional farmers as *their lower relative treatment costs offset their technical disadvantage*. All of these results are robust to changes in our empirical setting, including the addition of control variables or more abrupt adjustments.

These primary results about the effects of landscape composition on pest control are completed by secondary results about the effects of (i) pest pressure, (ii) difference in relative treatment costs, and (iii) treatment efficacy on free-riding. Specifically, higher pest pressure theoretically encourages both farmers to free-ride on smaller ranges of landscape shares, up to a point where they stop free-riding if the risk of contamination becomes too high. This effect appears in our data: the average organic and conventional farmer free-rides when managing less than about 11% and 47% of the landscape, respectively, when FD pressure is low (i.e., outside MCPs), *but never free-rides when FD pressure is high* within MCPs. Additional empirical results show that differences in treatment incentives – whether regarding the relative treatment costs estimated from vineyard prices or treatment efficacy estimated from rainfall intensity – affect the strategic behaviours of conventional and organic farmers too, but to a more limited extent (cross-sectional variations shifting the free-riding thresholds by up to a few percentage points only).

While the literature on the private control of mobile public bads is predominantly theoretical, our study bridges this gap by integrating both theoretical and empirical approaches. The primary theoretical contribution of our work lies in identifying *when* and *under what conditions* free-riding emerges for pest control in mixed organic-conventional landscapes. Previous studies have largely relied on dynamic, spatially explicit models in which pest control decisions are *strategic complements* (Reeling and Horan, 2015), a framework that tends to overlook the possibility of free-riding. Consequently, theoretical attention has often focused on pest eradication – an extreme corner solution – while the opposite corner solution – full free-riding, has been relatively neglected.[3] In contrast, we adopt a simpler, static, spatially-implicit framework where control decisions are *strategic substitutes*, naturally leading to equilibria characterized by free-riding behaviours (Fenichel et al., 2014; Reeling and Horan, 2015). Our model builds on prior research by incorporating differences in (i)

[3]Tsao and Costello (2024) discuss the "no-control" behaviour as an assumption rooted in model primitives, typically arising from high control costs or low private damage, rather than as an equilibrium outcome.

production value (Fenichel et al., 2014; Liu and Sims, 2016; Atallah et al., 2017; Costello et al., 2017) and (ii) treatment costs (Burnett, 2006; Costello et al., 2017), while further extending the analysis to include (iii) landscape shares and (iv) treatment efficacy – two dimensions that have received less attention but are critical to understanding strategic interactions in our context.

Our theoretical results also echo the literature on the private provision of public goods (particularly in agriculture; see, e.g., Hansen and Libecap, 2004; Pfeiffer and Lin, 2012), where pest control represents private contributions to the total control effort – a public good. In this context, Warr (1983)'s "neutrality" theorem – which posits that income redistribution does not affect total contributions – holds only if contributions remain interior, but not when constraints bind (as poorer individuals cease contributing; see Andreoni, 1988). This aligns with our findings for organic landscape shares: larger organic areas trigger strategic substitution (organic treatments replacing conventional ones), but free-riding arises as a corner solution when covered landscape shares become too unequal, with the small-area farmer type no longer controlling pests. Already identified as a key driver in historical public good problems like the Dust Bowl (Hansen and Libecap, 2004), we show that the size of managed areas is a key determinant of free-riding in pest control.

On the empirical side, we contribute to the literature by focusing on a specific pest and related insecticide use, enabling sound connections with theory. Our primary results complement those of Larsen et al. (2024) on insecticide use in mixed organic-conventional landscapes, which, to our knowledge, is the closest empirical study to ours.[4] Whereas Larsen et al. (2024) aggregated all insecticides together to estimate *marginal* strategic adjustments in treatment intensities, our results show that strategic interactions can push farmers to *fully* free-ride on others' control efforts for a given pest. Such a radical outcome – supported by theory – could not have been identified by Larsen et al. (2024) due to their aggregation. While concerning, our theory and empirical assessment indicate that these free-riding behaviours should stop when the organic landscape share increases, highlighting the key role of landscape composition in strategic pest control.

The paper is organized as follow. Section 2 presents the game-theory model and the theoretical propositions we derive from it. Section 3 describes the data and the econometric strategy used to test the theory. Section 4 displays the empirical results and Section 5 concludes.

[4]Additional empirical approaches include Singerman and Useche (2019) and Lence and Singerman (2023), who focus on coordination failure in a collective pest management program in Florida within a framed field experiment.

# 2 A model of strategic interactions in mixed landscapes

This section presents the epidemiological pest model (Section 2.1), the induced strategic interactions between conventional and organic farmers (Section 2.2), and the theoretical propositions detailing the influence of different parameters on these interactions (Section 2.3).

## 2.1 Epidemiological pest model

We consider a spatially-implicit epidemiological model to describe pest contamination in a landscape composed of exogenous shares $S$ of organic farming (tagged $o$) and $(1-S)$ conventional farming (tagged $c$), each belonging to a specific representative farmer (namely one organic and one conventional farmer).[5] The only endogenous decision variables are the landholding proportion each farmer treats against the pest, respectively denoted by $t^o$ and $t^c$ ("treatment intensity" henceforth). From a pest-control point of view, there are thus three parts in the landscape: (i) the proportion treated with organic treatments (equal to $St^o$), (ii) that treated with conventional treatments ($(1-S)t^c$) and (iii) the remaining untreated proportion ($S(1-t^o)+(1-S)(1-t^c)$), tagged by $u$ when convenient.

Farmers' treatments have both a local and global effect on pest pressure. First, pesticides decrease the risk of contamination on treated land, a private benefit. Second, treatments reduce the global public bad pressure, by preventing (part of) the local pests from spreading over the whole landscape. Defining (i) the risk of primary infection $\alpha$, (ii) treatment efficacy $\gamma^j$, for $j=\{o,c,u\}$, with $\gamma^u=0$ and $0<\gamma^o\leq\gamma^c$, and (iii) the pest diffusion rate $\delta$ generating a risk of secondary infection, the level of public bad $\varphi(t^o,t^c)$ in our model is given by the following function of the treatment levels (a full mathematical derivation is provided in Section A.1 of OA):

$$\varphi(t^o,t^c)=\frac{\alpha}{1-\delta}-\frac{\delta}{1-\delta}\left(St^o\gamma^o+(1-S)t^c\gamma^c\right). \tag{1}$$

This level corresponds to the maximal potential public bad level $\frac{\alpha}{1-\delta}$ – i.e., what would happen with no control at all in the landscape – *diminished* by the (weighted) effect of *organic and conventional treatments* (equivalent to a spatial spillover of treatment effects over the landscape in our model). This effect is proportional to the overall treatment level – the public good *per se*, denoted $\Gamma$ – to

[5] This simplifying assumption is made to ease the interpretation of the results. The $n+m$ farmers case is treated in Section A.3 of the Online Appendix (OA) and tested for sensitivity analysis in the empirical part of the paper.

which farmers contribute by treating:

$$\Gamma(t^o, t^c) = St^o\gamma^o + (1-S)t^c\gamma^c. \tag{2}$$

The level of public bad (Equation (1)) corresponds to the latent risk of contamination of untreated land. Without further assumption, its value can be negative (full eradication) or greater than one (certain contamination).[6] We assume, without loss of generality, that $0 < \alpha, \delta, \gamma^o, \gamma^c < 1$ and restrict the possible cases assuming that:

**Assumption 1** (Contamination is not certain)**.** *Even if there is no treatment in the landscape, contamination is not certain, in the sense that* $\varphi(0,0) < 1 \Leftrightarrow \alpha + \delta < 1$.

The latent risk is locally diminished by the efficacy of the treatment used (if any) and translates into a probability of infection $\eta^j$ for each landscape part $j = \{o, c, u\}$:

$$\eta^j(t^o, t^c) = \begin{cases} 0 & \text{if} \quad \varphi(t^o,t^c) - \gamma^j < 0, \\ \varphi(t^o,t^c) - \gamma^j & \text{if} \quad 0 \le \varphi(t^o,t^c) - \gamma^j \le 1. \end{cases} \tag{3}$$

## 2.2 Strategic interactions for pest control

### 2.2.1 Farmers' program and treatment decisions

Organic and conventional farmers aim to maximize their expected payoff by choosing treatment intensity $t^o$ and $t^c$ respectively, with $0 \le t^j \le 1$. Assuming risk-neutrality, $\forall (j,k) \in \{o,c\}^2$, $j \ne k$, farmer $j$'s payoff-per-area is:

$$\pi^j(t^j|t^k) = t^j \underbrace{\Big((1-\eta^j(t^o,t^c))R^j - c^j\Big)}_{\text{payoff-per-area for treated land}} + (1-t^j) \underbrace{(1-\eta^u(t^o,t^c))R^j}_{\text{payoff-per-area for untreated land}}, \tag{4}$$

where $R^j$ is the revenue-per-area without pest damage, and $c^j$ the treatment cost. We assume that this cost is not prohibitive in the following sense:

**Assumption 2.** *Pesticide treatment is cost-effective in the sense that* $\gamma^j > \frac{c^j}{R^j}$.

Without this assumption, treatment is never economically interesting because of relative pesticide inefficacy (whatever the probability of infection).

[6] A representation of the public bad level as a function of treatment levels is provided in Figure A1 of OA.

Equation (4) shows that each farmer's payoff depends on the other's decision through the probability of infection $\eta^j$, which depends on the public bad level (see Equation (3)). This interdependence creates strategic interactions between the two farmers. In the static game, both farmers simultaneously choose their treatment intensity $t^j$ to maximize their payoff, resulting in a Nash equilibrium $(t^{o\ eq}, t^{c\ eq})$. The combined treatments constitute a public good $\Gamma^{\ eq}$ to which the farmers contribute differently, not only due to possible strategic effects, but also to differences in landscape shares and treatment efficacy (see Equation (2)).

### 2.2.2 Best strategies and game equilibrium

Each farmer's best response depends on the public bad level $\varphi(t^o, t^c)$ and associated risk of contamination, requiring us to consider three different areas in the strategy space $[0,1]^2$ to determine $(t^{o\ eq}, t^{c\ eq})$. Depicted in Figure A.1 and fully explored in Section A.1 of OA, we only provide the intuitions behind these different ranges of treatment levels below.

First, reasoning by contradiction, the equilibrium cannot be in the range of (high) treatment levels leading to a full eradication (i.e., $\varphi(t^o, t^c) < 0$). In that case, both farmers' best responses would be not to treat ($t^j = 0$), which is inconsistent with condition $\varphi(t^o, t^c) < 0$ as $\varphi(0,0) > 0$.

Second, whenever $\varphi(t^o, t^c) > \gamma^j$ (i.e., if treatment does not fully protect from contamination), farmer $j$'s payoff is linear in the treatment decision (see Section A.2 in OA) implying a corner solution as best-response. Under Assumption 2, the farmer fully treats ($t^j = 1$), whenever this strategy is still consistent with the condition $\varphi(t^o, t^c) > \gamma^j$ ; otherwise, the solution belongs to the next case.

Whenever $0 \leq \varphi(t^o, t^c) \leq \gamma^j$, the best responses correspond to interior solutions with:

$$\begin{cases} t^{o*}(t^c) = \frac{\alpha-(1-\delta)\frac{c^o}{R^o}+\delta(S\gamma^o-(1-S)\gamma^c t^c)}{2\delta S\gamma^o}, \\ t^{c*}(t^o) = \frac{\alpha-(1-\delta)\frac{c^c}{R^c}+\delta((1-S)\gamma^c-S\gamma^o t^o)}{2\delta(1-S)\gamma^c}. \end{cases} \tag{5}$$

Equation (5) shows that these best-response functions are decreasing in the other farmer's effort. That is, treatments are *strategic substitutes* in our model. Accordingly, there is a single (strategic) equilibrium at the intersection of the two functions:

$$(t^{o\ eq}, t^{c\ eq}) = \left(\frac{\alpha-(1-\delta)(2\frac{c^o}{R^o}-\frac{c^c}{R^c})+\delta(2S\gamma^o-(1-S)\gamma^c)}{3\delta S\gamma^o}, \frac{\alpha-(1-\delta)(2\frac{c^c}{R^c}-\frac{c^o}{R^o})+\delta(2(1-S)\gamma^c-S\gamma^o)}{3\delta(1-S)\gamma^c}\right). \tag{6}$$

Such a Nash equilibrium results in zero probabilities of infection on treated land, but in a positive probability on untreated land.

Treatment intensities are constrained by the condition $0 \leq t^j \leq 1$, meaning that there are parameter values for which corner solutions occur. In particular, the Nash equilibrium in Equation (6) corresponds to an interior solution with strictly positive treatment levels for both farmers if $S \in ]S_{min}, S_{max}[$, with:

$$S_{min} \equiv \frac{-\alpha + \delta\gamma^c + (1-\delta)(2\frac{c^o}{R^o} - \frac{c^c}{R^c})}{\delta(2\gamma^o + \gamma^c)}, \tag{7}$$

$$S_{max} \equiv \frac{\alpha + 2\delta\gamma^c - (1-\delta)(2\frac{c^c}{R^c} - \frac{c^o}{R^o})}{\delta(\gamma^o + 2\gamma^c)}. \tag{8}$$

Outside this range, only one of the two farmers treats – and we obtain corner solutions $(t^{j*}(0), 0)$ defined by the best-response functions in Equation (5) when the other farmer does not treat.

The corner solution $t^{j*} = 1$ occurs if the risk of primary infection $\alpha$ is too high. Farmer $j$ fully treats for $S \geq \frac{\alpha - (1-\delta)(2\frac{c^j}{R^j} - \frac{c^k}{R^k}) - \delta\gamma^c}{\delta(\gamma^o - \gamma^c)}$ if $\alpha \geq \bar{\alpha}^j$, with:

$$\bar{\alpha}^j \equiv \delta\gamma^o + (1-\delta)\left(2\frac{c^j}{R^j} - \frac{c^k}{R^k}\right), \tag{9}$$

and fully treats whatever $S$ if $\alpha > \bar{\bar{\alpha}}^j$, with:

$$\bar{\bar{\alpha}}^j \equiv \delta\gamma^c + (1-\delta)\left(2\frac{c^j}{R^j} - \frac{c^k}{R^k}\right). \tag{10}$$

Equation (6) characterizes the Nash equilibrium for all $S \in ]S_{min}, S_{max}[$ only when $\alpha < \min(\bar{\alpha}^o, \bar{\alpha}^c)$. As soon as one of these levels is exceeded (noting that $\bar{\alpha}^j \leq \bar{\bar{\alpha}}^j$ under our assumption that $\gamma^o \leq \gamma^c$) farmer $k$'s best response would be $t^{k*}(1)$ (subject to $0 \leq t^k \leq 1$). Whenever the primary infection is too high for both farmers, the landscape is fully treated, leading to full eradication.

## 2.3 Propositions from comparative statics

We analyse how the main parameters affect the previously described strategic interactions, considering the respective effects of (i) the organic landscape share $S$ (Section 2.3.1), (ii) risk of primary infection $\alpha$ (Section 2.3.2), (iii) difference in relative treatment costs $c^j/R^j$ (Section 2.3.3) and (iv) difference in treatment efficacy $\gamma^j$ (Section 2.3.4). Section 2.3.5 investigates combined effects.

### 2.3.1 Influence of organic landscape share

To study the influence of the organic landscape share on free-riding, we consider the Nash equilibrium depicted in Equation (6) as a function of $S$ and derive some propositions. Proposition 1 specifically states the landscape conditions under which a farmer fully free-rides, while Proposition

2 refers to the effects of landscape composition on the strategic substitution when both farmers treat. The results in Propositions 1 and 2 are derived for the general case but illustrated in Figure 1 for the specific case without differences in economic or technological characteristics, as a benchmark to analyse the effect of these differences on strategic pest control interactions later on.

**Proposition 1** (Organic landscape share and free-riding)**.** *The organic farmer does not treat if $S \leq S_{min}$ (defined in Equation (7)), and the conventional farmer does not treat if $S \geq S_{max}$ (defined in Equation (8)), i.e., when managing less than a share $1 - S_{max}$ of the landscape.*

*Proof of Proposition 1.* This is a direct consequence of the condition $t^j \geq 0$ ($j \in \{o, c\}$) used in the derivation of the strategic equilibrium in Section 2.2.2, leading to the landscape share thresholds $S_{min}$ (Equation (7)) and $S_{max}$ (Equation (8)). □

Proposition 1 states that the best strategy of a farmer managing a small landscape share is to free-ride.[7] Whenever the organic landscape share is such that $S_{min} < S < S_{max}$, both farmers treat according to the Nash equilibrium depicted in Equation (6), with a clear substitution effect.

**Proposition 2** (Organic landscape share and strategic substitution)**.** *Whenever $S_{min} < S < S_{max}$, the proportion of the landscape treated with organic treatment (i.e., $t^{o\ eq}(S)S$) increases linearly with $S$, while the proportion of the landscape treated with conventional treatment (i.e., $t^{c\ eq}(S)(1-S)$) decreases linearly with $S$.*

*Proof of Proposition 2.* Within the range of landscape shares $S_{min} < S < S_{max}$, both farmers treat according to Equation (6). Multiplying these treatment intensities by corresponding landscape shares gives the proportion of landscape treated for each farming type, i.e., $St^{o\ eq}(S) = \frac{\alpha-(1-\delta)(2\frac{c^o}{R^o}-\frac{c^c}{R^c})+\delta(2S\gamma^o-(1-S)\gamma^c)}{3\delta\gamma^o}$ for organic farming, which is linear and increasing in $S$, and $(1-S)t^{c\ eq}(S) = \frac{\alpha-(1-\delta)(2\frac{c^c}{R^c}-\frac{c^o}{R^o})+\delta(2(1-S)\gamma^c-S\gamma^o)}{3\delta\gamma^c}$ for conventional farming, which is linear and decreasing in $S$. □

Proposition 2 means that, within the range of landscape shares where both farmers treat, there is a *strategic substitution* between treated areas when the landscape composition changes.[8] When farmers have the same technology (i.e., when $\gamma^o = \gamma^c$), there is a *perfect strategic substitution*

[7] When farmers have similar costs, revenues and technologies, one has $1 - S_{max} = S_{min}$, i.e., both farmers free-ride for a similar range of landscape shares (as shown in the right-hand-side panel of Figure 1).

[8] Note that the linear response of treated areas to landscape composition is not due to constant treatment intensities. The larger the landscape share managed by a farmer, the larger their treatment intensity, as $\frac{dt^{o\ eq}}{dS} = \frac{-\alpha+\delta\gamma^c+(1-\delta)(2\frac{c^o}{R^o}-\frac{c^c}{R^c})}{3\delta\gamma^o S^2} \geq 0$ for $\alpha \leq \bar{\bar{\alpha}}^o$ and $\frac{dt^{c\ eq}}{dS} = \frac{\alpha-\delta\gamma^o-(1-\delta)(2\frac{c^c}{R^c}-\frac{c^o}{R^o})}{3\delta\gamma^c(1-S)^2} \leq 0$ for $\alpha \leq \bar{\alpha}^c$.

between the two farmers, such that the total treated areas – and thus the public good level defined in Equation (2) – does not depend on the organic landscape share between $S_{min}$ and $S_{max}$.

Figure 1 illustrates the way treatment strategies at the Nash equilibrium change when the organic landscape share varies from 0 to 1 for an illustrative set of parameters. The left-hand-side panel represents the strategy space $[0,1]^2$ and depicts the best-response functions and corresponding Nash equilibrium (marked "NE") for the illustrative case $S = 0.2$, when farmers have no economic or technological differences (with $c^o = c^c$, $R^o = R^c$, and $\gamma^o = \gamma^c$). It also shows the implicit curve along which the equilibrium shifts as $S$ varies, along with the equilibrium locus for $S = 0.5$ and $S = 0.8$ (specific illustrations for these levels of $S$ are provided in Figure A2 of OA). The right-hand-side panel of Figure 1 plots the areas treated by the two farmers at the landscape scale (solid lines) as a function of $S$, as well as the corresponding treatment intensities (dashed lines). These figures illustrate the free-riding behaviour of farmers managing a small share of the landscape (Proposition 1), as well as the strategic substitution pattern when both treat (Proposition 2).[9]

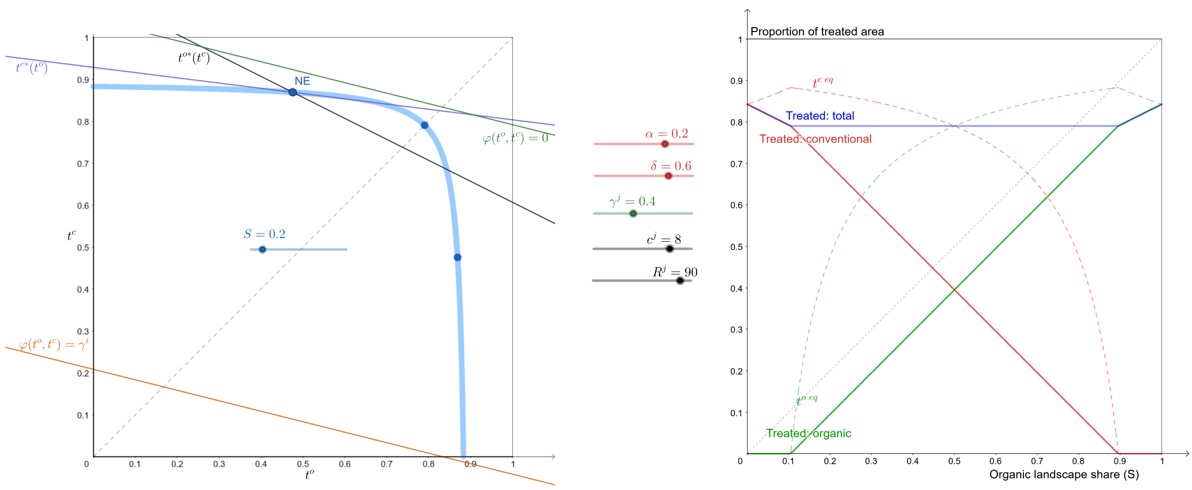


Figure 1: Effect of landscape composition on the Nash equilibria for pest control.

NOTE. The left-hand-side panel displays the best response functions and corresponding strategic equilibrium (NE) for farmers having identical treatment cost, farm revenue, and treatment efficacy for a specific organic landscape share $S = 0.2$ (other parameters values are displayed in the Figure). The blue concave and decreasing curve is an implicit function of $S$ that depicts all possible equilibrium loci when varying $S$, highlighting where the equilibrium would be for $S = 0.5$ (on the 45° line) and $S = 0.8$ (symmetrical to $S = 0.2$ with respect to the 45° line). The orange line corresponds to the isovalue of public bad at level $\varphi(t^o, t^c) = \gamma^o$, and the green line corresponds to the limit for eradication $\varphi(t^o, t^c) = 0$. An interactive version of the figure is available at https://www.geogebra.org/m/m8xgcbty. The right-hand-side panel displays the resulting treatment levels as a function of $S$ for the same set of other parameters. The proportion of the landscape treated with organic (green) and conventional (red) treatments – as well as the sum of the two (blue) – are displayed in solid lines, along with corresponding treatment intensities (dashed curves). An interactive version of the figure is available at https://www.geogebra.org/m/gztxym9k.

[9]Note that conventional treatment intensity increases with the share of organic farming within the range of landscape shares where free-riding occurs, i.e., $t^{o\ eq}(0)$ rises with $S$ for $S < S_{min}$. This aligns with evidence of higher treatment intensities on conventional fields adjacent to organic ones, as observed by Larsen et al. (2024). In our model, this pattern arises solely from conventional farmers' efforts to compensate for organic free-riding.

### 2.3.2 Influence of pest pressure

In practice, the risk of primary infection $\alpha$ is likely to differ between locations. The following proposition characterizes its influence on the strategic interactions and resulting equilibrium.

**Proposition 3** (Pest pressure)**.** *The larger the risk of primary infection $\alpha$, the smaller the range of landscape shares for which a farmer free-rides (i.e., the lower $S_{min}$ and the larger $S_{max}$).*

*Proof of Proposition 3.* From Equation (7), we can deduce that $S_{min}$ decreases with $\alpha$, i.e., $\frac{dS_{min}}{d\alpha} < 0$. From Equation (8), we deduce that $S_{max}$ increases with $\alpha$, i.e., $\frac{dS_{max}}{d\alpha} > 0$. □

This result is illustrated in Figure 2.[10] Proposition 3 implies that when the risk of contamination is high enough, neither of the two farmers free-ride. If $\alpha \geq \bar{\bar{\alpha}}^o$ (defined in Equation (10)), the organic farmer never free-rides in the sense that $S_{min} \leq 0$. Likewise, if $\alpha \geq \bar{\alpha}^c$, the conventional farmer never free-rides, in the sense that $S_{max} \geq 1$. Free-riding behaviours are triggered by low pest pressures.

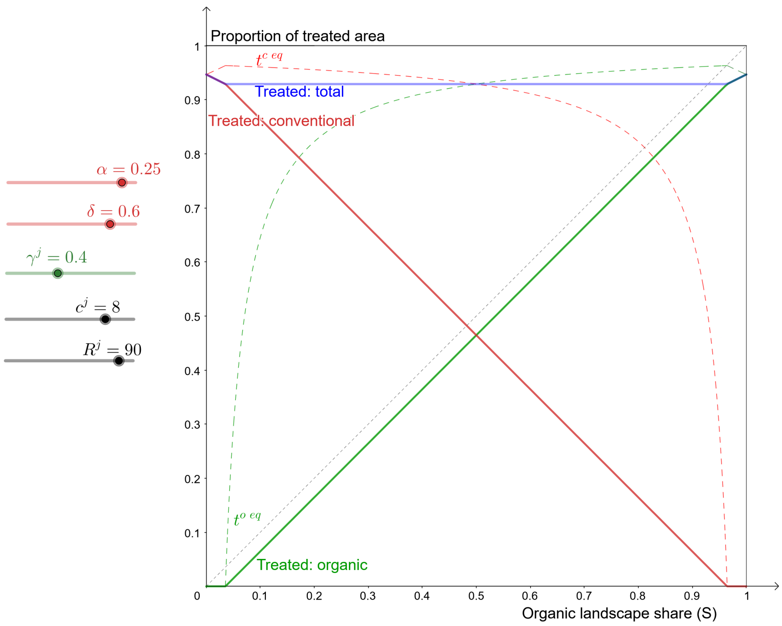


Figure 2: Effect of pest pressure.
NOTE. Proportions of the landscape treated with organic (green) and conventional (red) treatments – as well as the sum of the two (blue) – in solid lines, along with corresponding treatment intensities (dashed curves) as a function of organic landscape share $S$ for high pest pressure ($\alpha = 0.25$) compared to Figure 1. The values of the other parameters are displayed within the Figure. An interactive version of the figure is available at https://www.geogebra.org/m/gztxym9k.

### 2.3.3 Influence of relative treatment costs

The free-riding thresholds in Equations (7) and (8) depend on the relative treatment costs $\frac{c^j}{R^j}$. This ratio can differ between farmers because their revenues $R$ or treatment costs $c$ differ, generating different incentives to protect crops. There is no reason, however, to assume *a priori* that this ratio

[10] The effect of pest pressure on farmers' best response functions and corresponding Nash equilibrium can be retrieved by varying $\alpha$ in the interactive version of Figure 1.

is larger for one type of farmer. For example, in our empirical application, organic treatment is more costly than conventional treatment, but FD infection – which kills vines irrespectively of whether they are organically or conventionally managed – induces larger losses for organic vineyards (given their higher value; see Corsi and Strøm, 2013). To isolate the effect of a *difference* in economic incentives *between the two farmers*, we derive the following benchmark result (considering that they have the same pesticide efficacy but different relative costs).

**Benchmark Result 1** (Difference in relative treatment costs: isolated effect)**.** *With similar technologies, the farmer with the higher relative treatment cost* $\frac{c^j}{R^j}$ *would free-ride for a larger range of landscape shares.*

*Proof of Benchmark Result 1.* Assume that farmers have similar technologies $\gamma$ but different relative treatment costs $\frac{c^j}{R^j}$. Rewriting Equation (7), $S_{min}$ can be expressed as a linear function of the relative treatment costs as $S_{min} = a+b(2\frac{c^o}{R^o}-\frac{c^c}{R^c})$, with constants $a$ and $b > 0$ that depend on parameters $\alpha, \delta$ and $\gamma$. Similarly, for the conventional farmer, we have $1-S_{max} = a+b(2\frac{c^c}{R^c}-\frac{c^o}{R^o})$. Taking the difference between the two ranges of free-riding, we obtain $S_{min} - (1 - S_{max}) = 3b\left(\frac{c^o}{R^o} - \frac{c^c}{R^c}\right)$, which has the same sign as the difference in the relative treatment costs. □

Benchmark Result 1 identifies a first asymmetry in the free-riding pattern: if organic and conventional farmers had the same treatment efficacy, a lower relative treatment cost for the organic farmer would imply that they free-ride for a smaller range of landscape shares. Figure 3 illustrates such an asymmetry. In practice, however, this effect would interact with the effect of treatment efficacy and cannot be tested in isolation (see Section 2.3.5).

Apart from Benchmark Result 1, we can analyse how the free-riding thresholds vary across situations characterized by different pairs of relative treatment costs $\left(\frac{c^o}{R^o}, \frac{c^c}{R^c}\right)$.[11]

**Proposition 4** (Comparative statics on the relative treatment costs)**.** *The larger* $\left(2\frac{c^j}{R^j} - \frac{c^k}{R^k}\right)$, ceteris paribus*, the larger the range of landscape shares for which farmer j free-rides.*

*Proof of Proposition 4.* Equation (7) shows that $S_{min}$ is linearly increasing with $(2\frac{c^o}{R^o}-\frac{c^c}{R^c})$, whereas Equation (8) shows that $S_{max}$ is linearly decreasing with $\left(2\frac{c^c}{R^c} - \frac{c^o}{R^o}\right)$. □

Proposition 4 makes it possible to assess how the free-riding thresholds change across situations characterized by different levels of relative costs $(\frac{c^o}{R^o}, \frac{c^c}{R^c})$. For example, while a decrease in the

[11] Whereas Benchmark Result 1 was comparing the free-riding thresholds of the two farmers when their relative treatment cost differs one from the other but imposing identical technologies, here we compare the free-riding threshold of a given farmer between two different situations with different relative treatment costs. The technologies of the two farmers can be different, but are assumed not to change between the two situations.

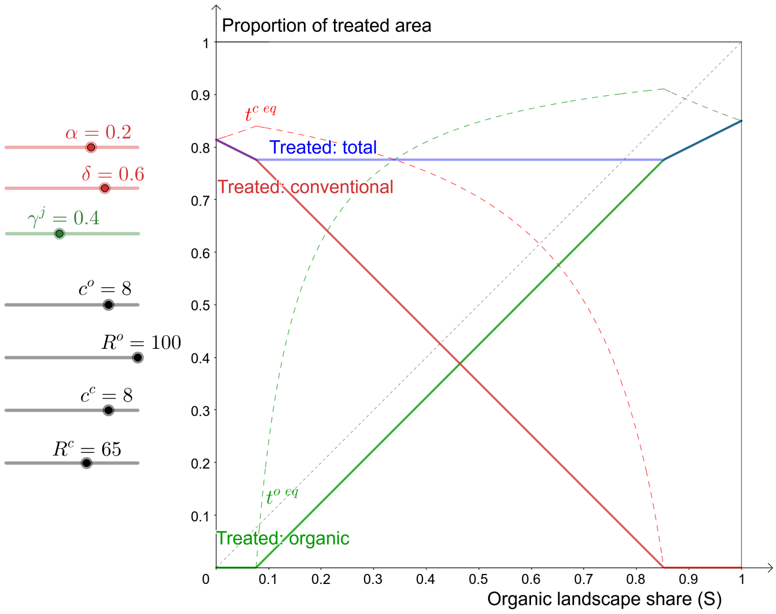


Figure 3: Effect of different relative treatment costs.
NOTE. Proportions of the landscape treated with organic (green) and conventional (red) treatments – as well as the sum of the two (blue) – in solid lines, along with corresponding treatment intensities (dashed curves) as a function of organic landscape share $S$ when the two farmers have different revenues (with $R^o > R^c$) but the same technology and cost. The values of the other parameters are displayed within the Figure. An interactive version of the figure is available at https://www.geogebra.org/m/vvkbwruy.

relative treatment costs would unequivocally reduce the ranges of landscape shares for which both farmers free-ride *when they have the same relative treatment costs*, this is not necessarily true *when their relative treatment costs differ*. Denote the difference in farmer $j$'s relative treatment cost between the two situations as $\Delta \frac{c^j}{R^j} = \left(\frac{c^j}{R^j}\right)_2 - \left(\frac{c^j}{R^j}\right)_1$. If the cost decreases (i.e., $\Delta \frac{c^j}{R^j} < 0$), that farmer can still free-ride for a larger range of landscape shares in situation 2 than in situation 1 if $\Delta \frac{c^j}{R^j} > \frac{1}{2} \Delta \frac{c^k}{R^k}$ – i.e., if the reduction in this farmer's relative treatment cost is less than half that of the other.[12] Our empirical analyses exploiting spatial heterogeneity in average revenues allow us to characterize which condition prevails in our case study (see Section 4.3).

### 2.3.4 Influence of treatment efficacy

The technology parameter $\gamma^j$ also influences the free-riding thresholds.[13] The following benchmark result emphasizes how a difference in the treatment efficacy taken in isolation – i.e., for equal relative treatment costs – generates an asymmetry in the free-riding pattern.

[12] Symmetrically, a farmer facing an increase in relative treatment costs may end up free-riding for a smaller range of landscape shares if the increase for the other farmer is twice as big.

[13] A difference in treatment efficacy also influences the strategic substitution pattern. When $\gamma^o \neq \gamma^c$, strategic substitution is no more perfect and the public good level changes proportionally to the gap in treatment efficacy as the organic farming share increases, according to $\frac{d\Gamma}{dS} = \frac{1}{3}(\gamma^o - \gamma^c)$. To see this, plug the equilibrium level of treatment of Equation (6) into the $\Gamma$ expression of Equation (2) and derive it with respect to $S$: $\frac{d\Gamma}{dS} = \frac{d(St^o\gamma^o)}{dS} + \frac{d((1-S)t^c\gamma^c)}{dS} = \frac{2\gamma^o + \gamma^c}{3} + \frac{(-2\gamma^c - \gamma^o)}{3} = \frac{1}{3}(\gamma^o - \gamma^c)$.

**Benchmark Result 2** (Difference in treatment efficacy: isolated effect)**.** *With similar relative treatment costs, the farmer with the lowest treatment efficacy $\gamma^j$ would free-ride on a larger range of landscape shares.*

*Proof of Benchmark Result 2.* Assume that $\frac{c^o}{R^o} = \frac{c^c}{R^c} = \frac{c}{R}$ but $\gamma^o \neq \gamma^c$, so that $S_{min} = \frac{-\alpha+\delta\gamma^c+(1-\delta)\frac{c}{R}}{\delta(2\gamma^o+\gamma^c)}$ and $1 - S_{max} = 1 - \frac{\alpha+2\delta\gamma^c-(1-\delta)\frac{c}{R}}{\delta(\gamma^o+2\gamma^c)} = \frac{-\alpha+\delta\gamma^o+(1-\delta)\frac{c}{R}}{\delta(\gamma^o+2\gamma^c)}$. If $\gamma^o < \gamma^c$, one has $-\alpha + \delta\gamma^c + (1-\delta)\frac{c}{R} > -\alpha + \delta\gamma^o + (1-\delta)\frac{c}{R}$ and $\delta(2\gamma^o + \gamma^c) < \delta(\gamma^o + 2\gamma^c)$, implying $\frac{-\alpha+\delta\gamma^c+(1-\delta)\frac{c}{R}}{\delta(2\gamma^o+\gamma^c)} > \frac{-\alpha+\delta\gamma^o+(1-\delta)\frac{c}{R}}{\delta(\gamma^o+2\gamma^c)}$ and thus $S_{min} > 1 - S_{max}$. □

Benchmark Result 2 identifies a second source of asymmetry in the free-riding pattern: if organic treatments are less effective than conventional treatments (i.e., $\gamma^o < \gamma^c$), one would have $S_{min} > 1 - S_{max}$ (notwithstanding the effect of differences in the cost and revenue parameters). Figure 4 illustrates a case of treatment efficacy asymmetry, with $\gamma^o < \gamma^c$. In practice, however, this effect would interact with the effect of differences in relative treatment costs described in Benchmark Result 1 and cannot be tested in isolation.

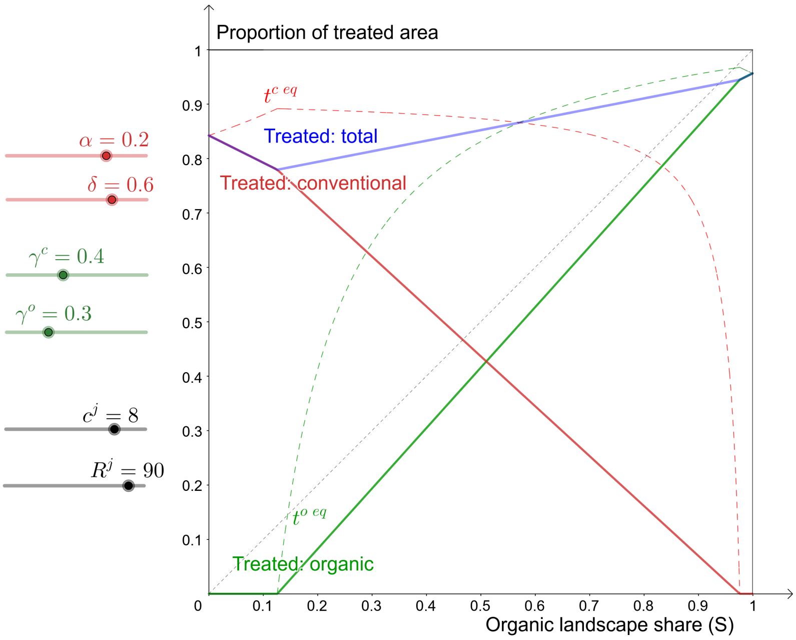


Figure 4: Effect of different treatment efficacy.
NOTE. Proportions of the landscape treated with organic (green) and conventional (red) treatments – as well as the sum of the two (blue) – in solid lines, along with corresponding treatment intensities (dashed curves) as a function of organic landscape share $S$ when the two farmers have different technologies (with $\gamma^o < \gamma^c$) but the same revenue and cost. The values of the other parameters are displayed within the Figure. An interactive version of the figure is available at https://www.geogebra.org/m/nkxduedr.

We can however analyse how the free-riding threshold of a given farmer varies across situations characterized by different treatment efficacy pairs $(\gamma^o, \gamma^c)$. In practice, treatment efficacy is likely to vary spatially for both farmers, for example with pedoclimatic conditions (e.g., rainfall leaching out applied pesticides). The way this heterogeneity would affect free-riding depends on the *relative* *change in treatment efficacy between farmers*, as well as on the *differences in relative treatment costs*, as stated in the following proposition.[14]

**Proposition 5** (Decrease in treatment efficacy)**.** *A decrease in treatment efficacy from* $(\gamma_1^o, \gamma_1^c)$ *to* $(\gamma_2^o, \gamma_2^c)$*, with* $\gamma_1^j > \gamma_2^j$*, induces an increase of the range of landscape shares for which farmer* $j$ *free-rides if*

$$\underbrace{\frac{-\alpha + (1-\delta)\left(2\frac{c^j}{R^j} - \frac{c^k}{R^k}\right)}{\delta}\left(\frac{1}{(2\gamma_2^j + \gamma_2^k)} - \frac{1}{(2\gamma_1^j + \gamma_1^k)}\right)}_{>0 \text{ } if \text{ } \alpha<(1-\delta)\left(2\frac{c^j}{R^j} - \frac{c^k}{R^k}\right)} + \underbrace{\frac{\gamma_2^j}{2\gamma_2^j + \gamma_2^k} - \frac{\gamma_1^j}{2\gamma_1^j + \gamma_1^k}}_{>0 \text{ } if \text{ } \frac{\gamma_2^j}{\gamma_1^j} > \frac{\gamma_2^k}{\gamma_1^k}} > 0, \tag{11}$$

*and a decrease otherwise.*

*Proof of Proposition 5.* Consider the change in threshold $S_{min}$ when the treatment efficacy decreases for both farmers (possibly in a different way) from $(\gamma_1^o, \gamma_1^c)$ to $(\gamma_2^o, \gamma_2^c)$, with $\gamma_1^j > \gamma_2^j$:

$$\begin{aligned} S_{min}^2 - S_{min}^1 &= \frac{-\alpha + (1-\delta)\left(2\frac{c^o}{R^o} - \frac{c^c}{R^c}\right) + \delta\gamma_2^o}{\delta(2\gamma_2^o + \gamma_2^c)} - \frac{-\alpha + (1-\delta)\left(2\frac{c^o}{R^o} - \frac{c^c}{R^c}\right) + \delta\gamma_1^o}{\delta(2\gamma_1^o + \gamma_1^c)} \\ &= \frac{-\alpha + (1-\delta)\left(2\frac{c^o}{R^o} - \frac{c^c}{R^c}\right)}{\delta}\underbrace{\left(\frac{1}{(2\gamma_2^o + \gamma_2^c)} - \frac{1}{(2\gamma_1^o + \gamma_1^c)}\right)}_{>0 \text{ when } \gamma_2^j<\gamma_1^j} + \underbrace{\frac{\gamma_2^o}{2\gamma_2^o + \gamma_2^c} - \frac{\gamma_1^o}{2\gamma_1^o + \gamma_1^c}}_{\geq 0 \text{ if} \frac{\gamma_2^o}{\gamma_1^o} \geq \frac{\gamma_2^c}{\gamma_1^c}}. \end{aligned}$$

A similar result can be derived for $(1 - S_{max})$, *mutatis mutandis.* □

Proposition 5 means that a reduction in treatment efficacy affecting both farmers increases free-riding for farmer $j$ if Equation (11) is satisfied. Whenever the change in treatment efficacy affects both farmers in the same proportion, i.e., $\frac{\gamma_2^c}{\gamma_1^c} = \frac{\gamma_2^o}{\gamma_1^o}$ (which includes the case of identical technologies with $\gamma^o = \gamma^c$), the range of landscape shares over which farmer $j$ free-rides would increase if $\alpha < (1-\delta)\left(2\frac{c^j}{R^j} - \frac{c^k}{R^k}\right)$. When the decrease in pesticide efficacy affects the two farmers differently, free-riding increases more for the farmer whose treatment efficacy decreases relatively less.[15] Our empirical analyses exploiting cross-sectional variation in average rainfall indicate that the conventional farmer is more affected in practice (see Section 4.3).

[14] Even when both farmers have identical relative treatment costs and treatment efficacy, the effect of a decrease in treatment efficacy is ambiguous and would increase the free-riding thresholds only if $\alpha < (1-\delta)\frac{c}{R}$.

[15] A decrease in treatment efficacy could have the counter-intuitive effect of decreasing free-riding *if the risk of primary infection* $\alpha$ *is large enough*, in particular for the farmer who is more affected by the reduction in pesticide efficacy.

### 2.3.5 Asymmetric free-riding pattern: Combined effects

Our game theory analyses show that farmers managing a small-enough landscape share should free-ride on the other's pest control efforts (Proposition 1). Differences in relative treatment costs or in treatment efficacy create an asymmetry in the free-riding pattern. The farmer with the higher relative treatment cost has an incentive to free-ride for a larger range of landscape shares (Benchmark Result 1), as does the farmer with the lower treatment efficacy (Benchmark Result 2). The two effects interact in a complex way and can act in synergy or antagonism (depending on the parameter values), according to the difference $(1 - S_{max}) - S_{min} = \frac{-\alpha+\delta\gamma^o+(1-\delta)\left(2\frac{c^c}{R^c}-\frac{c^o}{R^o}\right)}{2\gamma^c+\gamma^o} - \frac{-\alpha+\delta\gamma^c+(1-\delta)\left(2\frac{c^o}{R^o}-\frac{c^c}{R^c}\right)}{2\gamma^o+\gamma^c}$. If this expression is positive, the parameters are such that the conventional farmer free-rides for a larger range of landscape shares than the organic farmer. This is the case whenever the following condition (simply obtained by simplifying and rearranging terms) holds:

$$
\begin{aligned}
& (1 - S_{max}) - S_{min} > 0 \\
\Leftrightarrow \quad & \underbrace{\left(2\delta - \frac{\alpha}{\gamma^o+\gamma^c}\right)(\gamma^o - \gamma^c)}_{\text{pure technology effect}} + \underbrace{4(1-\delta)\left(\frac{c^c}{R^c} - \frac{c^o}{R^o}\right)}_{\text{pure cost effect}} + \underbrace{(1-\delta)\left(\frac{\frac{c^c}{R^c}\gamma^o - \frac{c^o}{R^o}\gamma^c}{\gamma^o+\gamma^c}\right)}_{\text{mixed effect}} > 0. \qquad (12)
\end{aligned}
$$

When $\gamma^c \geq \gamma^o$, it will never be the case if $\frac{c^c}{R^c} \leq \frac{c^o}{R^o}$, i.e., when the conventional pesticide is both more effective and relatively less costly. It can be the case when the two effects go in opposite direction, with $\frac{c^c}{R^c} > \frac{c^o}{R^o}$, i.e., when the conventional treatment is more effective but also relatively more costly, as the coefficient of the pure cost effect is likely to be larger than that of the pure technology effect.

# 3 Empirical methods

Equipped with Propositions 1 to 5 and combined effects, the rest of the paper consists of assessing them empirically for the case of FD control in French vineyards. This section describes data compilation for all French postcodes with vineyards in 2017 (Section 3.1) and provides some empirical procedures for testing the propositions with cross-sectional econometrics (Section 3.2).

## 3.1 Data sources

We compiled diverse data from several sources. The outcome variables — the areas treated with organic and conventional insecticides — are calculated based on official statistics on insecticide sales from 2017 (Section 3.1.1). We merged them with background variables about organic and conventional vineyard areas in 2020, FD pressure in 2017, vineyard prices in 1995, and average cumulative rainfall from 1990 to 2010 (Section 3.1.2).[16] The final dataset of 1,228 postcodes is presented in Section 3.1.3.

### 3.1.1 Insecticide sales

To calculate the areas covered by organic and conventional treatments against FD in each postcode, we combine (i) postcode-level insecticide sales from the *Banque Nationale des Ventes de produits phytopharmaceutiques par les Distributeurs agréés* (BNVD),[17] (ii) the list of approved insecticides against FD from the French *National Agency for Food, Environmental and Job Health Safety* (ANSES) and (iii) the recommended dosage per hectare from each product label.

Only one insecticide, *pyrevert*, is approved against FD for organic farming and has no other significant use on vineyards or other crops. Since there is no biological control solution to eliminate leafhoppers, the quantities of *pyrevert* purchased are expected to provide a reliable measure of organic treatments against FD.

By comparison, ANSES approves 108 insecticides against FD for conventional farming (many of which are rarely sold), and some of them can also be used for other crops or diseases. Our strategy to limit measurement errors on our conventional treatment estimates consists in restricting the conventional insecticides *specifically used* for FD control. For this purpose, we balance (i) the selection of approved products purchased in postcodes *with MCPs* (see footnote 2) that have *more than 70% of their agricultural area dedicated to vineyards* (i.e., the "specialized postcodes" henceforth), and (ii) the deletion of products purchased in postcodes *without vineyards*. Further detailed in Section B.1 of OA, this strategy is expected to balance type I errors from including an insecticide that is not used against FD (*false positive*) and type II errors from excluding a used insecticide (*false negative*). To minimize type I errors, our preferred analyses restrict the list to the 10 most-used insecticides in specialized postcodes with MCPs – $N = 10$, according to the notations of Section B.1 in OA – for which less than 0.1% are purchased in postcodes without vineyards ($\sigma = 0.1$). This procedure is expected to work for our conventional treatment estimations as vineyards are concentrated in France – as confirmed by sensitivity analyses with other restricted lists (for $N \in \{10, 15, 20\}$ and $\sigma \in \{0.5, 5, 100\}$; see Section 4.2).

[16] As explained below, our most recent information on MCPs (and thus FD pressure) at the national level comes from 2017. We matched this data with insecticide sales in the same year and use vineyard areas from the nearest agricultural census (available once every ten years, thus in 2020). Vineyard prices are from 1995 to limit endogeneity with FD pressure. Average past rainfall is chosen to reflect farmers' expectations about treatment efficacy.

[17] This yearly database created by the French government publicly available from 2014 compiles information on all pesticides and active substances *purchased* for France, at the postcode level of the head offices of buyers.

### 3.1.2 Background variables

We merge the insecticide purchase data with several other postcode-level datasets. Using the 2020 French agricultural census, we calculate the total vineyard area (organic and conventional combined). Additionally, we use data on organic vineyard area in 2020 from the French *Agency for the Development of Organic Agriculture*. Since vineyard area changes little from year to year, their ratio is expected to closely approximate the share of organic vineyards ($S$) for each postcode in 2017. Accordingly, we compute the proportion of vineyard area treated against FD with organic and conventional products.

To evaluate the influence of pest pressure (Section 2.3.2), we proxy the presence of MCPs within each postcode using a binary variable taking the value one if the postcode contains or is adjacent to an FD cluster, and zero otherwise – naturally, we expect pest pressure to be higher in the former than in the latter case. To quantify the influence of the relative treatment cost (Section 2.3.3), we use vineyard price as the capitalized value of wine revenue. Indeed, while the cost of insecticide is higher for organic farmers, this difference does not vary much over space and the relative treatment costs are expected to mainly (negatively) depend on revenues. Vineyard prices are available for the 370 French geographical indications (*Appellations d'0rigine Contrôlée*), and we downscale them to the postcode level from their spatial delineations obtained via the *French Institut National des Appellations d'Origine*. Finally, we assess the influence of treatment efficacy (Section 2.3.4) using average cumulative rainfall from 1990 to 2010, obtained via *Météo-France* – we expect that organic insecticide efficacy decreases more than that of conventional insecticides when rainfall increases.[18]

### 3.1.3 Final dataset

We end up with a cross-section of 1,228 postcodes with strictly positive vineyard area,[19] which represents 20% of all postcodes in mainland France. Tables B.1 and Figure B2 in OA report the main summary statistics. There are 783 postcodes for which the organic vineyard area is non-null, such that postcodes with mixed organic-conventional vineyards represent about two thirds of the total. The latter are however twenty times larger than those with conventional vineyards only (see the area-weighted summary statistics).

[18]The lower efficacy of *pyrevert* is well known from controlled trials (Chuche and Thiéry, 2014). This is due to its lack of persistence, such that it mostly acts on the insect populations at the time of treatment. By comparison, the effect of conventional insecticides lasts about two or three weeks.

[19]As FD monitoring changed after 2015, we only have access to reliable information on MCPs for the years 2016 and 2017. Given the additional limited short-term variability of insecticide use over time, we specifically restrict our regression sample to 2017. We use 2016 for robustness, accounting for potential insecticide storage from one year to another (expected to be minimal according to prior studies; see, e.g., Bareille et al., 2024).

In most postcodes, neither organic nor conventional farmers fully treat against FD, indicating potential widespread free-riding behaviours. Farmers treat about two thirds of the organic vineyard area on aggregate, against 112% of the conventional vineyard area.[20] Weighting these treated areas by the total organic and conventional areas, Table A1 in OA shows that 13% and 104% of all vineyards in France are treated with organic and conventional treatments respectively. Finally, summary statistics show significant spatial heterogeneity of production conditions, whether regarding FD exposure (MCPs), vineyard prices, or rainfall quantity. In particular, about half of the postcodes contain an MCP, suggesting that they are subject to higher FD pressure than others.

## 3.2 Econometric approach

We assess empirically our theoretical propositions using cross-sectional econometric analyses considering each postcode as a (long-term) strategic equilibrium. We present the empirical counterparts for primary Propositions 1 and 2 in Section 3.2.1, and for secondary Propositions 3, 4, and 5 in Section 3.2.2 respectively. Section 3.2.3 discusses the identifying restrictions.

### 3.2.1 Primary propositions

According to Propositions 1 and 2, a strategic farmer managing a sufficiently small landscape share should not use insecticides, but should treat increasingly when their covered area exceeds a given threshold (while the other farmers' treatment decreases). Exploiting sample variations in organic landscape share of French vineyards allows us to estimate both the free-riding thresholds $S_{min}$ and $S_{max}$ for the average organic and conventional farmers and the strategic substitution effect. Denoting $Y_i^j$ the vineyard share treated with insecticides of type $j$ in postcode $i$, we estimate the following model separately for organic ($j = o$) and conventional farmers ($j = c$):

$$\text{arcsinh}\left(Y_i^j\right) = \theta_0^j + \theta_1^j S_i + \boldsymbol{\theta}_2^{j\prime}\mathbf{X}_i + \epsilon_i^j, \tag{13}$$

where $\mathbf{X}_i$ is the centered vector of control variables (i.e., total vineyard area and other land-use areas), and $\epsilon_i^j$ is the remaining error. We estimate Equation (13) by weighted least squares (WLS), using the vineyard area of type $j$ in postcode $i$ as weight. To account for spatial auto-correlation of errors, we cluster the variance-covariance matrix across the 22 (highest administrative-level) French regions (Abadie et al., 2023).

[20] Conventional treatments are subject to measurement errors (see Section B.1 in OA). As such, the twelve additional percent points of treatments can be either seen as extra treatments, or as measurement errors.

The free-riding thresholds defined in Proposition 1 are obtained by setting $\hat{Y}^j = 0$ and $\mathbf{X} = 0$ for $j = \{o, c\}$, such that $\hat{S}_{min} = -\hat{\theta}_0^o/\hat{\theta}_1^o$ and $\hat{S}_{max} = -\hat{\theta}_0^c/\hat{\theta}_1^c$. The test below indicates that organic and conventional farmers free-ride on ranges of organic-conventional mixed landscapes if:

**Test 1** (Proposition 1)**.** *For* $j \in \{o, c\}$*:* $0 < -\hat{\theta}_0^j/\hat{\theta}_1^j < 1$.

From the same estimated coefficients of Equation (13), the substitution effect for treatments outside the free-riding areas theorized in Proposition 2 can be directly assessed from:

**Test 2** (Proposition 2)**.** *For* $0 \leq -\hat{\theta}_0^o/\hat{\theta}_1^o \leq S \leq -\hat{\theta}_0^c/\hat{\theta}_1^c \leq 1$*:* $\hat{\theta}_1^o \geq 0$ *and* $\hat{\theta}_1^c \leq 0$.

These two primary tests are defined for the average organic and conventional farmers by setting control variables to zero. We now turn to the test of the secondary propositions, moving away from such average conditions to investigate cross-sectional heterogeneity in free-riding behaviours.

### 3.2.2 Secondary propositions

We specifically test our secondary propositions by estimating the dependence of the free-riding thresholds on additional covariates, still from cross-sectional variations. The tests related to Propositions 3, 4, and 5 are based on the coefficients from:

$$\text{arcsinh}\left(Y_i^j\right) = \theta_0^j + \theta_1^j S_i + \boldsymbol{\theta}_2^{j\prime}\mathbf{X}_i + \theta_3^j MCP_i + \theta_4^j Price_i + \theta_5^j Rainfall_i + \epsilon_i^j. \tag{14}$$

The model now includes the variable $MCP_i$ (indicating the presence of at least one MCP in postcode $i$), $Price_i$ (corresponding to the average vineyard price), and $Rainfall_i$ (corresponding to the historical rainfall). By centering these variables, the tests of the primary propositions for average farmers remain unchanged, and secondary propositions are assessed by deviations from the average. Setting the control variables at their sample means ($\mathbf{X} = 0$), the effect of pest pressure, economic, and technological heterogeneity on free-riding thresholds are assessed from:

$$\hat{S}_{min} = -\left(\hat{\theta}_0^o + \hat{\theta}_3^o MCP + \hat{\theta}_4^o Price + \hat{\theta}_5^o Rainfall\right)/\hat{\theta}_1^o \tag{15}$$

$$\hat{S}_{max} = -\left(\hat{\theta}_0^c + \hat{\theta}_3^c MCP + \hat{\theta}_4^c Price + \hat{\theta}_5^c Rainfall\right)/\hat{\theta}_1^c. \tag{16}$$

The presence of an MCP in postcode $i$ (i.e., $MCP_i = 1$) indicates a more stringent FD pressure, which allows us to empirically assess the discrete decrease in free-riding coverage theorized by Proposition 3 – i.e., the decrease of $S_{min}$ and the increase of $S_{max}$ – when pest pressure increases according to:

**Test 3** (Proposition 3)**.** $-\hat{\theta}_3^o/\hat{\theta}_1^o \leq 0$ *and* $-\hat{\theta}_3^c/\hat{\theta}_1^c \geq 0$.

Cross-sectional vineyard price heterogeneity is expected to be the main source of cross-sectional differences for relative treatment costs. Higher vineyard prices are expected to reduce the relative treatment costs for both farmers, which can lead to an increase in free-riding for at most one type of farmer according to Proposition 4. It requires the following test to be *rejected*.

**Test 4** (Proposition 4)**.** $-\hat{\theta}_4^o/\hat{\theta}_1^o > 0$ *and* $-\hat{\theta}_4^c/\hat{\theta}_1^c < 0$ *(to be rejected).*

Because the price gap between organic and conventional wines is potentially large (as measured empirically; see, e.g., Corsi and Strøm, 2013) and because *we expect the revenue gap between organic and conventional farmers to increase with vineyard value*, an increase in average vineyard price can lead to $\Delta\frac{c^c}{R^c} > \frac{1}{2}\Delta\frac{c^o}{R^o}$, such that conventional farmers could free-ride on larger landscape shares, i.e., $-\hat{\theta}_4^c/\hat{\theta}_1^c < 0$ whatever the treatment choices of organic farmers.

As rainfall reduces treatment efficacy for both farmers (yet relatively more for organic farmers because of more leaching; see, e.g., GDON, 2014), we expect that the range of landscape shares for which both farmers free-ride increases with rainfall. Proposition 5 states that free-riding should increase even more for the farmer with the *higher relative treatment cost* and who is *less affected by the decrease in treatment efficacy*, i.e., the conventional farmer. The empirical counterpart of Proposition 5 is then:

**Test 5** (Proposition 5)**.** $-\hat{\theta}_5^c/\hat{\theta}_1^c < \hat{\theta}_5^o/\hat{\theta}_1^o < 0$.

Tests 1 to 5 are empirically assessable from the WLS estimation of Equations (13) and (14). The test 1 for the presence of free riding is related to proposition 1 as it allows us to estimate the free-riding thresholds defined in the theoretical model. Within these thresholds, Test 2 is a direct test of Proposition 2 on partial strategic substitution of pest control. Rejecting test 2 would contradict a key proposition of the theoretical model. The same applies to Test 3, which is a falsification test of Proposition 3 derived from our model. Under the assumption that higher vineyard prices increase the relative treatment cost for both farmers, Proposition 4 is empirically tested by Test 4. Since conventional farmers are assumed to have the higher relative treatment cost and to be less affected by the decrease in treatment efficacy, Test 5 amounts to a rejection of a constraint derived from the theoretical model (Proposition 5).

### 3.2.3 Identification strategy and related assumptions

Our empirical tests rely on the exploitation of cross-sectional variations in organic landscape shares and insecticide purchases across postcodes. Indeed, given the fact that FD spreads very slowly (mostly remaining contingent within a particular region in the long run),[21] farmers' FD exposure variations largely rely on their spatial dimension (instead of their temporal dimension). As for any other cross-sectional econometric analyses, our empirical tests can thus be threatened by endogenous bias risks. We discuss below why we believe that these risks are limited.

**Simultaneity.** A key assumption for the consistency of the estimations of our primary propositions is the pre-determination of the share of organically-farmed vineyard area out of the postcode total vineyard area. Because organic production requires a three-year conversion period, it is unlikely that farmers' organic area choice is directly driven by yearly variations of insecticide purchases against FD. This would imply that annual insecticide choices are anticipated three years in advance. Symmetrically, the exit from organic production following the presence of a FD cluster is not really credible as the organic area shares are not significantly different inside and outside MCPs ($p > 0.1$ in the corresponding Student test).

**Omitted variable bias.** The presence of omitted variables correlated with organic landscape shares and insecticide purchases is also an identification threat (e.g., unobserved regulatory, environmental, or economic conditions). The stability of the estimated free-riding thresholds between Equations (13) and (14) will put this risk into perspective. Indeed, we account for regulatory conditions with the MCPs in the postcode. We also account for average rainfall from 1990 and 2010, an exogenous variable correlated with many environmental ones. Finally, we use average vineyard price from 1995 (the first available year) as the average of each geographical indication (*Appellations d'Origine Contrôlée*), areas defined around the beginning of the 20$^{\text{th}}$ century. The variables associated with the secondary propositions are thus additional exogenous proxies for main omitted variables. Our results for the primary propositions are robust to their inclusion.

**Measurement errors.** While not threatening our estimation for organic treatment choices, measurement errors for conventional insecticide purchases can bias our analyses (see Section 3.1.1). Yet, these errors are first limited by the control variables relating to the other land-use areas. Including these areas allows us to attenuate the risk of using approved insecticides on other crops, under the assumption of constant application rates. Second, while our preferred analyses restrict the list of approved insecticides, mostly to minimize type I error (see Section 3.1.1), we additionally run sensitivity analyses including more conventional insecticides used (more marginally) against

[21] Adrakey et al. (2023) showed that the annual dispersal capacity of the FD vector results in contamination up to 300 m away from the source of infection. Vector mobility is expected to be mainly within postcodes, which have an average area of about 75 $km^2$ (i.e., approximately a circle of 5 km radius).

leafhoppers to relax type II errors. The results of these sensitivity analyses largely align with those of our preferred analyses.

**Aggregated purchases.** Our dataset reports insecticide purchases for organic and conventional farmers aggregated for the whole postcode. While these measurements match our two-(representative-)farmer theoretical setting, we cannot rule out that strategic interactions also occur within each farmers' group as BNVD does not distinguish purchases by farm.[22] Treating the multiple farmers case theoretically, Appendix A.3 shows that our propositions do hold with $n$ organic and $m$ conventional farmers (with $n \geq 1$ and $m \geq 1$), even if affecting the extent of free-riding. We empirically test for this potential confounding factor by additionally conditioning our estimations on the number of organic and conventional wine farmers in each postcode. The results of this sensitivity analysis largely align with those of our preferred analyses.

# 4 Empirical results

Section 4.1 presents the empirical results regarding our primary Propositions 1 and 2. Section 4.2 displays the results of some sensitivity analyses on these two propositions. Section 4.3 presents additional results regarding our secondary Propositions 3, 4, and 5.

## 4.1 Primary propositions

Table 1 provides the results of the estimation of Equation (13) separately for organic and conventional farmers. As explained in Section 3.2.1, the coefficients associated with the organic landscape share and with the constant allows us to empirically test whether the Propositions 1 and 2 consistently match the observed farmers' behaviour in real conditions.

Columns (1) and (2) of Table 1 show that Propositions 1 and 2 are empirically supported for organic farmers: The constant is negative and the coefficient associated with $S$ positive, with $0 < -\hat{\theta}_0^o/\hat{\theta}_1^o < 1$. . This means that organic farmers first free-ride on the contributions of conventional farmers until $S$ reaches the theoretical threshold of $S_{min}$, and then increasingly treat as $S$ increases. Our results from column (2) indicate that such a theoretical threshold is reached for a value of

[22] Bareille et al. (2024) highlights that the small size of the average French postcode (around 75 km$^2$) makes BNVD one of the most precise pesticide purchase databases globally (notably in its spatial resolution).

Table 1: Impacts of $S$ on insecticides used by organic and conventional farmers

| | **Organic** | | **Conventional** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constant | -0.054 | -0.086 ** | 0.835 *** | 0.770 *** |
| | (0.011) | (0.015) | (0.022) | (0.027) |
| | [0.041] | [0.039] | [0.180] | [0.226] |
| $S$ | 0.861 ** | 0.913 *** | -1.140 | -1.367 ** |
| | (0.045) | (0.047) | (0.206) | (0.207) |
| | [0.301] | [0.298] | [0.694] | [0.651] |
| Controls | No | Yes | No | Yes |
| $R^2$ | 0.322 | 0.332 | 0.024 | 0.067 |
| Observations | 783 | 783 | 1,228 | 1,228 |

NOTE. The table reports the estimates of the share of organic vineyards in the vineyard landscape $S$ on the inverse hyperbolic sine transformation of insecticides used against FD by organic and conventional farmers in 2017. Estimates in columns (1) and (2) are weighted by the organic vineyard areas. Estimates in columns (3) and (4) are weighted by the conventional vineyard areas. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to heteroscedasticity-robust standard errors reported in ordinary brackets, we report clustered standard errors at the wine region level in square brackets. *, **, *** respectively indicate p-values lower than 0.1, 0.05 and 0.01 using clustered standard errors.

$S_{min} = 0.086/0.913 \approx 9\%$ (with centered control variables). These results are robust to the drop of control variables about total vineyard and other land-use areas in the postcode.[23]

Columns (3) and (4) of Table 1 show that Propositions 1 and 2 are also empirically verified for conventional farmers: the constant is positive and the coefficient associated with $S$ is negative, with $0 < -\hat{\theta}_0^c/\hat{\theta}_1^c < 1$. . Conventional farmers do treat some vineyards when there are no organic farmers ($S = 0$), and treatment decreases with $S$. Conventional farmers start to free-ride on organic farmers' efforts when $S$ reaches the theoretical threshold of $S_{max} = 0.770/1.367 \approx 56\%$ with centered control variables (and 73% without control variables). This proportion is virtually unobserved in our sample (only 38 observations out of 1,228 exceed this threshold), so that estimates of this value are very imprecise.

Table 1 also documents an interesting substitution pattern between organic and conventional farmers as $S$ increases between $S_{min} < S < S_{max}$. Specifically, organic farmers' treatments *compensate* the decrease in conventional farmers' treatments, but *only to some extent* (by a factor of 0.7 for 1). Indeed, an increase of 0.1 in $S$ when $S_{min} < S < S_{max}$ leads organic farmers to treat additional $0.1 \times 0.913 \approx 9\%$ of the landscape (see results from column (2) in Table 1), while the

[23]Our results from column (1) indicate rather a threshold of about $0.054/0.861 \approx 6\%$ (without control variables), which remains a similar magnitude. This implies that the addition of controls about total vineyard area and alternative land uses in the estimation only marginally change the results.

conventional farmers decrease the treated area by about 14% (see results from column (4) in Table 1). This means that, at the margin, an increase in the share of organic vineyards in the landscape leads the overall landscape to be less treated, as shown in Figure C1 in OA.[24]

In a similar thought exercise, column (2) in Table 1 indicates that organic farmers would protect 0.913-0.086 ≈ 83% of the landscape in the (hypothetical) case where all vineyards were organic (i.e., $S$=1). Similarly, column (4) indicates that conventional farmers would protect about 77% of the area when $S$=0. Given the substitution mechanisms between organic and conventional treatments, this result suggests that the total treated areas in the landscape are almost constant (yet slightly increasing when $S > S_{max}$), amounting to about 65-80% on average, leaving about 20-35% of the vineyards untreated. These roughly constant treated areas at the landscape scale appear in Figure C1 in OA, where the confidence interval surrounding the total (organic + conventional) treatments always include 75% of the total landscape area.

### 4.2 Sensitivity analyses

The results above show that farmers do engage in strategic free-riding for pest control in real conditions. Either type of farmer seems to free-ride on the other type's efforts when managing a minor part of the landscape – when organic and conventional farmers respectively occupy less than 9% and 44% of the landscape ($S_{min}$ = 0.09 and $S_{max}$ = 0.56). Although consistent with our theoretical propositions, these results may not reflect true strategic behaviours but might instead be due to some of the empirical settings.

To test the robustness of our primary propositions, we estimate the impact of organic landscape share on both conventional and organic farmers' treatments with alternative specifications regarding (i) the transformation of the outcome variables (Section C.2 in OA), (ii) potential measurement errors on conventional treatments (Section C.3 in OA), (iii) controlling for the strategic interactions induced by the number of organic and conventional farmers (Section C.4 in OA), (iv) cross-section from 2016 instead of 2017 (Section C.5 in OA), (v) looking at extensive or intensive margin responses only (Sections C.6 and C.7 in OA) or (vi) examining treatment intensity instead of total treatment at the landscape scale (Section C.8 in OA). As detailed in the OA, all of our results are robust to these alternative empirical choices. We consistently find that $S_{min}$ falls between 7% and 10% (both with or without controls), but find a more uncertain level for $S_{max}$, falling between 55% and 75%

[24]This result is however only valid for $S_{min} < S < S_{max}$. Because conventional farmers start to free-ride for $S > S_{max} \approx 0.56\%$, an increase in the share of organic vineyards beyond this threshold leads the organic farmers to increase the aggregated proportion of landscape treated against FD vectors.

when including controls (and between 70% and 100% without controls). This lack of precision is explained by the limited number of observations with high $S$.

### 4.3 Secondary propositions

Now that we have empirically assessed our primary theoretical propositions for the average French farmer, we assess the consistency of our secondary propositions. Table 2 displays changes in organic and conventional farmers' treatments when organic landscape share changes from Equation (14), adding all elements related to Tests 3, 4, and 5.

Table 2: Impacts of $S$ on insecticides used by organic and conventional farmers with heterogeneous production conditions

| | **Organic** | | **Conventional** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constant | -0.093 * | -0.095 * | 0.674 *** | 0.723 *** |
| | (0.011) | (0.014) | (0.019) | (0.022) |
| | [0.053] | [0.053] | [0.078] | [0.101] |
| $S$ | 0.895 *** | 0.896 *** | -1.156 ** | -1.354 ** |
| | (0.043) | (0.046) | (0.163) | (0.163) |
| | [0.299] | [0.306] | [0.437] | [0.421] |
| MCP | 0.141 *** | 0.141 *** | 0.660 *** | 0.690 *** |
| | (0.015) | (0.016) | (0.032) | (0.033) |
| | [0.012] | [0.012] | [0.150] | [0.159] |
| Prices | -0.001 | -0.001 | -0.041 *** | -0.040 *** |
| | (0.004) | (0.004) | (0.005) | (0.005) |
| | [0.006] | [0.006] | [0.014] | [0.014] |
| Rainfall | -0.001 * | -0.001 * | -0.009 *** | -0.010 *** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| | [0.001] | [0.001] | [0.003] | [0.003] |
| Controls | No | Yes | No | Yes |
| R2 | 0.412 | 0.408 | 0.405 | 0.422 |
| Observations | 770 | 770 | 1,194 | 1,194 |

Note. The table reports the estimates of the share of organic vineyards in the vineyard landscape $S$ on the inverse hyperbolic sine transformation of insecticides used against FD by organic and conventional farmers in 2017 (we drop postcode without organic acreages in the first columns). Estimates in columns (1) and (2) are weighted by the organic vineyard areas. Estimates in columns (3) and (4) are weighted by the conventional vineyard areas. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using clustered standard errors.

**Test of Proposition 3.** Columns (1) and (2) of Table 2 show that Proposition 3 is empirically supported for organic farmers. Both the estimates associated with MCP are positive and the coefficients for the primary propositions (i.e., associated with the constant and $S$) remain of similar signs and magnitudes as in Table 1, implying $-\hat{\theta}_3^o/\hat{\theta}_1^o \leq 0$. When FD pressure is high (i.e., $MCP = 1$), estimates from column (2) suggest that organic farmers never free-ride because $S_{min} = (0.095 - 0.141)/0.896 < 0$ (see Equation (16)). When FD pressure is low (i.e., $MCP = 0$), organic farmers free-ride to a larger extent (more than in our primary propositions), until they represent about $S_{min} = 0.095/0.896 \approx 11\%$ of the landscape.

Columns (3) and (4) indicate that Proposition 3 is also empirically supported for conventional farmers. Both the estimated coefficients associated with MCP are positive and the coefficients associated with the constant and $S$ remain of similar signs and magnitudes as in Table 1, implying $-\hat{\theta}_3^c/\hat{\theta}_1^c \geq 0$. When FD pressure is low, our estimates from column (4) suggest that conventional farmers start to free-ride when organic farmers represent at least about $S_{max} = 0.723/1.354 \approx 53\%$ of the landscape. This indicates larger strategic interactions between the two farmer types when FD pressure is low, with only a small segment – for $S$ between 11% and 53% – for which both treat (partially) against FD. When FD pressure is high, results from column (4) suggest that conventional farmers always treat (i.e., $S_{max} = (0.723 + 0.690)/1.354 > 1$), revealing that the two farmers types never free-ride when FD pressure is high.

**Test of Proposition 4.** Table 2 shows that Test 4 is rejected as required, providing empirical support to Proposition 4. Columns (1) and (2) show that variations in average vineyard prices entail no significant shifts in organic treatments – i.e., null effect of $\hat{\theta}_4^o$ in Equation (15). By comparison, columns (3) and (4) show a negative impact of prices on conventional treatments, indicating that conventional farmers free-ride for a larger range of landscape shares in situations with lower relative treatment costs. According to our theoretical results, this suggests that conventional relative treatment costs decrease less rapidly than organic relative treatment costs as the revenue increases. Our estimates from column (4) suggest that $S_{max} \equiv 0.723/1.354 \approx 53\%$ for the average farmer (compared to 56% for our primary proposition), but that, when price increases by 10%, they free-ride since $S_{max} \equiv (0.723 - 1.100 \times 0.77 \times 0.041)/1.354 \approx 51\%$. That is, changes in prices do affect the scope of the conventional farmers' free-riding behaviour, but to a relatively small extent (two percentage points).

**Test of Proposition 5.** Table 2 empirically supports Proposition 5. The coefficients associated with rainfall are indeed significantly negative for both organic and conventional farmers, and $-\hat{\theta}_5^o/\hat{\theta}_1^o > 0$ and $-\hat{\theta}_5^c/\hat{\theta}_1^c < 0.$, suggesting that they free-ride for larger ranges of landscape shares when treatment efficacy decreases. Yet, as theoretically predicted, the increase in free-riding is larger for conventional than organic farmers, the former (i) being less affected by the decrease in treatment efficacy and (ii) having the lowest relative treatment cost (as confirmed by the empirical results for Proposition 4). Our estimates from columns (2) and (4) suggest that a rainfall increase of 10% increases organic farmers' free-riding by about $0.1 \times 0.001 \times 63.44/0.896 \approx 0.7\%$, against about 4.7% for conventional farmers.

## 5 Concluding remarks

This paper uses a game theory framework to explore strategic interactions for pest control in mixed organic-conventional landscapes. Our theoretical analysis suggests that landscape composition – i.e., the proportion of the landscape occupied by organic farming – is a key driver of pest control strategies. While the type of farmer occupying a larger share of the landscape has a greater incentive to control pests *ceteris paribus*, we show that the other type may eventually free-ride on this effort if its share of the landscape is sufficiently small. The organic landscape share thresholds that delineate these free-riding behaviours are analytically determined and shown to be influenced by (i) pest pressure, (ii) differences in relative treatment costs and (iii) difference in efficacy between organic and conventional treatments. Our theoretical results highlight the complexity of strategic interactions for pest management in mixed organic-conventional landscapes.

We empirically validate our theoretical propositions with exhaustive postcode-level data on organic and conventional farmers' treatment purchases against FD in French vineyards. Organic farmers are shown to fully free-ride on conventional farmers' efforts until they occupy about 9% of the landscape, beyond which their own efforts (partially) substitute reduction in conventional farmers' treatments. Although a precise estimate is difficult due to the lack of landscapes dominated by organic farming, conventional farmers are shown to fully free-ride on organic farmers' treatments when they occupy less than 44% of the landscape. However, as it appears from the theory, both types of farmer stop free-riding when pest pressure is high enough. Differences in relative treatment cost and efficacy only affect the strategic interactions to a more modest extent empirically.

Though applied to the specific FD case, our results have broader implications for understanding strategic interactions for pest control in other contexts. Like other pests and biological invasions, FD presence is a mobile public bad that spreads within the landscape and causes heterogeneous damage depending on farmers' characteristics and treatment choices. While slow diffusion and high damage are specific to FD, these features are shared by other pests like *Black Dead Arm* in vineyards and *Erwinia amylovora* in pear orchards, making our findings relevant beyond the FD context.

Our results have implications for pest control policies. While organic farming is widely promoted by policymakers for its positive environmental impacts, concerns exist about its potential detrimental effects on pest pressure. Our findings indicate that organic farming development is indeed likely to increase pest pressure during the early stage of its development, because their small share of the landscape provides a strong incentive for organic farmers to free-ride on conventional farmers' efforts. However, when organic farming expands, efforts to control pests with organic treatment would increase, supported by the incentives provided by the higher value of organic vineyards, and in spite of less effective treatments. As such, our results indicate that, in the medium term, such concerns may not be theoretically nor empirically supported.

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# Online Appendices (OA)

NOTE. The material contained herein is supplementary to the article entitled "Strategic free-riding for pest control in organic-conventional mixed landscapes".

## A Theoretical model: mathematical details

### A.1 Public bad as a function of treatment levels

**Computation of the equilibrium latent risk.** The local latent risk of contamination is the sum of three elements: i) the risk of primary infection $\alpha$, ii) the effect of the local treatment, which decreases the local risk by $\gamma^j$ for $j = \{o, c\}$,[A1] and iii) a secondary risk of infection due to diffusion of the public bad within the landscape, which corresponds to a share $\delta$ of the latent risk of contamination over the whole landscape.

Note that the only difference between the latent risk of an untreated plot and a treated one is the effect of the local treatment, as all plots face the same risk of primary and secondary infection. Denoting the latent risk of contamination of an untreated plot as $\varphi$ (which corresponds to the public bad level), we can thus write that of a treated plot as $\varphi - \gamma^j$ for $j = \{o, c\}$. The latent risk $\varphi$ is then the equilibrium of the following condition:

$$\varphi = \alpha + \delta \left( S(t^o(\varphi - \gamma^o) + (1 - t^o)\varphi) + (1 - S)(t^c(\varphi - \gamma^c) + (1 - t^c)\varphi) \right).$$

Developing all the terms, simplifying, and isolating $\varphi$, we obtain the following expression for the public bad, which corresponds to Equation (1):

$$\varphi(t^o, t^c) = \frac{\alpha - \delta(St^o\gamma^o + (1 - S)t^c\gamma^c)}{1 - \delta}.$$

**Latent risk in the strategy space.** The linearity of $\varphi(t^o, t^c)$ with respect to $t^o$ and $t^c$ means that treatments are substitutes in our framework. Given equation ((1)) and assumption 1, we can draw the map of the public bad level as a function of treatment levels, and identify the corresponding areas of contamination risk (see Figure A1). Considering the isovalue levels of public bad $\varphi(t^o, t^c) = \gamma^o$

[A1] As time and space are not accounted for explicitly in the model, preventing us from determining the local pest population at the time of pesticide application, it is easier to assume that pesticide reduces latent risk by a given amount than to assume it affects a share of the pest population. This is a realistic assumption if the pesticide is long-lasting and the pest moves, or if the treatment decision corresponds to a sequence of pesticide applications over time, affecting more than the local population at a given time.

and $\varphi(t^o, t^c) = \gamma^c$, we obtain four areas of risk, described from the upper-right (large values of $(t^o, t^c)$) to the lower-left (low values of $(t^o, t^c)$): An area with $\varphi(t^o, t^c) < 0$ in which the pest is eradicated; An area with $0 < \varphi(t^o, t^c) < \gamma^o$ in which only untreated plots are at risk; An area with $\gamma^o < \varphi(t^o, t^c) < \gamma^c$ in which both untreated and organic treated plots are at risk; An area with $\gamma^c < \varphi(t^o, t^c) < 1$ in which all plots are at risk.

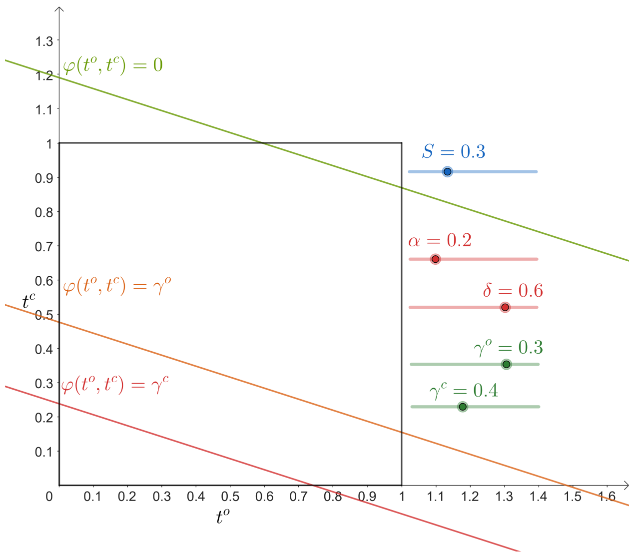


Figure A1: Example of isovalue levels of public bad $\varphi(t^o, t^c)$ in the strategy space. The x-axis corresponds to organic treatment level $t^o$, the y-axis to conventional treatment level $t^c$. Parameter values are tagged on the figure. An interactive version of the figure is available at https://www.geogebra.org/calculator/dbzretne

## A.2 Best-response strategies

Under Assumption 1 (which excludes a certain contamination of untreated plots), there are three cases to consider for farmer $j$: either i) no plot is at risk when $\varphi(t^o, t^c) \leq 0$, or ii) all plots are at risk (treated or not) when $\varphi(t^o, t^c) > \gamma^j$, or iii) only untreated plots are at risk when $0 < \varphi(t^o, t^c) \leq \gamma^j$.

In the no-risk case, the best strategy for both farmers would be not to treat. This cannot correspond to an equilibrium as $\varphi(0, 0) > 0$ when $\alpha > 0$. There is no equilibrium in this area of the map.

In the "full-risk" case, the farmer's profit can be written as $\pi^j = t^j \left((1 - \varphi + \gamma^j)R^j - c^j\right) + (1 - t^j)((1 - \varphi)R^j)$. Simplifying and using the expression of $\varphi(t^o, t^c)$, we can note that the profit is linear in the treatment decision $t^j$. The decision to fully treat ($t^j = 1$) or not treat at all ($t^j = 0$) depends on the sign of $\gamma^j R^j(1 + \frac{\delta}{1-\delta}\mathbf{B}^j) - c^j$, where $\mathbf{B}^o = S$ and $\mathbf{B}^c = 1 - S$. Under Assumption

2, this expression is positive whatever $S$. The farmer thus has an incentive to fully treat. Note that this result can lead to an actual full treatment strategy for farmer $o$ (resp. farmer $c$) only if $\varphi(t^o, t^c) > \gamma^o$ (resp. $> \gamma^c$) for $(t^o, t^c) = (1, 0)$ (resp. $(0, 1)$).[A2] Otherwise, the incentive to treat as much as possible in this case leads the public bad level to the other case.

In the "partial risk" case, the farmer's profit can be written as

$$\pi^j = t^j \left(R^j - c^j\right) + (1 - t^j)((1 - \varphi)R^j).$$

This equation is no longer linear in $t^j$ and there is an interior solution to the optimization problem. Classical optimization leads to the following best response function of each player:

$$t^{j*}(t^k) = \frac{\alpha - \frac{c^j}{R^j}(1-\delta) + \delta\left(\mathbf{B}^j\gamma^j - \mathbf{B}^k\gamma^k t^k\right)}{2\delta\gamma^j\mathbf{B}^j}, \qquad \text{A1}$$

corresponding to Equation (5). Isolating $t^k$ from this equation gives an alternative expression $\tilde{t}^k(t^j)$, which can be equalized to its counterpart $t^{k*}(t^j)$ to characterize the equilibrium provided in Equation (6).

The positivity constraint $t^j \geq 0$ is equivalent to a condition on $S$ that defines the free-riding thresholds provided in Equation (7) and Equation (8). The constraint $t^j \geq 1$ results in a condition on $S$ that may not be satisfied for $\alpha \geq \bar{\alpha}^j$, and that in never satisfied for $\alpha \geq \bar{\bar{\alpha}}^j$.

Figure A2 illustrates how the Nash equilibrium changes when $S$ changes, in complement to Figure 1.

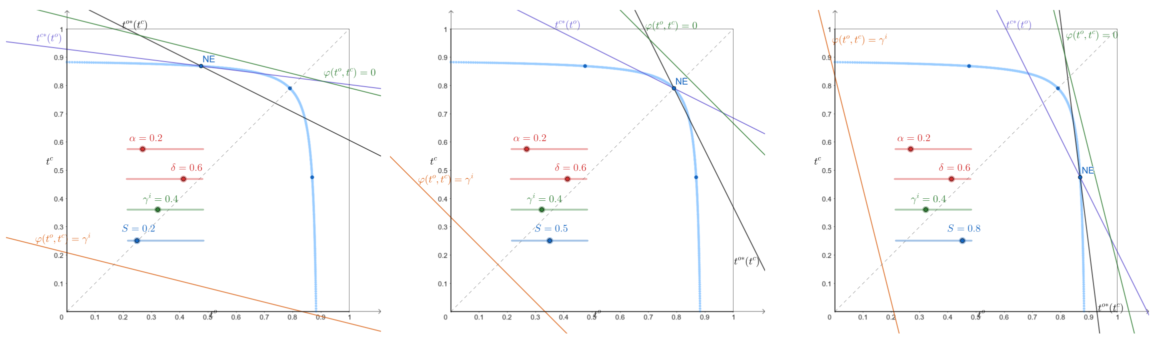


Figure A2: Best response functions and corresponding strategic equilibrium (NE) for symmetrical farmers. Left-hand-side panel: $S = 0.2$ ; Central panel: $S = 0.5$ ; Right-hand-side panel : $S = 0.8$. All figures depict the equilibrium curve as a function of $S$ (light-green, concave and decreasing curve). An interactive version of the figure is available at https://www.geogebra.org/m/m8xgcbty

[A2] This depends on the intersect of the isovalue public bad lines with the axis in Figure A1.

### A.3 The $n+m$ farmers case

To study the robustness of our results to the number of farmers, we now relax the "representative farmers" assumption and consider that there are $n$ organic farmers and $m$ conventional farmers. Within each group, however, farmers are assumed to be identical, i.e., to have the same economic incentives, technology and landscape share. An organic farmer thus manages a share $S/n$ of the landscape, and a conventional farmer a share $(1-S)/m$.

We provide the derivation of the equilibrium for the multi-farmers case, detailing the computation of the best response function for the organic farmers case only; the derivation for the conventional farmers would follow the same steps.

The profit of a given organic farmer adopting treatment level $\tilde{t}^o$ when the other farmers adopt treatment levels $t^o$ and $t^c$ is

$$\pi^o = \tilde{t}^o\,(R^o - c^o) + (1-\tilde{t}^o)\Big(1 - \underbrace{\frac{\alpha - \delta((\frac{S}{n}\tilde{t}^o + \frac{(n-1)S}{n}t^o)\gamma^o + (1-S)t^c\gamma^c)}{1-\delta}}_{\varphi(\tilde{t}^o,t^o,t^c)}\Big)R^o.$$

Profit maximization yields

$$\tilde{t}^{o*}(t^o,t^c) = \frac{\frac{\alpha}{\delta} - \frac{(1-\delta)}{\delta}\frac{c^o}{c^o} + \frac{S}{n}\gamma^o - \frac{(n-1)}{n}S\gamma^o t^o - (1-S)\gamma^c t^c}{2\gamma^o S/n}.$$

As organic farmers are symmetrical in all respects, the equilibrium of the organic farmers' strategies must satisfy $\tilde{t}^o = t^o$, and we obtain the organic farmers' best response function

$$t^{o*}(t^c) = \frac{\alpha - \frac{c^o}{R^o}(1-\delta) + \delta\left(\frac{S}{n}\gamma^o - (1-S)\gamma^c t^c\right)}{\frac{n+1}{n}S\delta\gamma^o}.$$

For the conventional farmers, we obtain the corresponding expression

$$t^{c*}(t^o) = \frac{\alpha - \frac{c^c}{R^c}(1-\delta) + \delta\left(\frac{(1-S)}{m}\gamma^c - S\gamma^o t^o\right)}{\frac{m+1}{m}(1-S)\delta\gamma^c}.$$

Solving for equilibrium treatment levels give

$$\begin{aligned} t^{o\ eq} &= \frac{\alpha - (1-\delta)\left((m+1)\frac{c^o}{R^o} - m\frac{c^c}{R^c}\right) + \delta(\frac{m+1}{n}S\gamma^o - (1-S)\gamma^c)}{\frac{n+m+1}{n}\delta S\gamma^o}, \\ t^{c\ eq} &= \frac{\alpha - (1-\delta)\left((n+1)\frac{c^c}{R^c} - n\frac{c^o}{R^o}\right) + \delta(\frac{n+1}{m}(1-S)\gamma^c - S\gamma^o)}{\frac{n+m+1}{m}\delta(1-S)\gamma^c}. \end{aligned}$$

Positivity constraints $t^{j\ eq} \geq 0$ on the treatment intensities lead us to define the multi-player free-riding thresholds

$$
\begin{aligned}
S_{min} &= \frac{-\alpha + \delta\gamma^c + (1+\delta)\left((m+1)\frac{c^o}{R^o} - m\frac{c^c}{R^c}\right)}{\delta(\frac{m+1}{n}\gamma^o + \gamma^c)}, \\
S_{max} &= \frac{\alpha + \frac{n+1}{m}\delta\gamma^c - (1+\delta)\left((n+1)\frac{c^c}{R^c} - n\frac{c^o}{R^o}\right)}{\delta(\gamma^o + \frac{n+1}{m}\gamma^c)}.
\end{aligned}
$$

All our propositions remain qualitatively valid.

Moreover, we can derive the following effects related to the number of farmers.

A. Increasing both the number $n$ of organic farmers and the number $m$ of conventional farmers while keeping $n = m$ increases the range of landscape shares for which there is free-riding, i.e., increases $S_{min}$ and decreases $S_{max}$.

B. Increasing the number of one type of farmer makes this category free-ride on a larger range of landscape shares, while making the other category free-ride on a smaller range of landscape shares: The organic landscape share threshold $S_{min}$ under which organic farmers free-ride increases with $n$ – the number of organic farmers, but decreases with $m$ – the number of conventional farmers ; Likewise, the threshold $S_{max}$ above which conventional farmers free-ride decreases with $m$, but increases with $n$.

Overall, the more farmers of one type, the lower their best-response treatment, due to a dilution of the perceived benefit of treating: each farmer fails to account for the beneficial effect of individual treatment for peers, just as it was overlooked for the other category of farmer. This effect is partly compensated for by an increased treatment in the other group, due to the strategic interaction nature of our problem. This results in an overall equilibrium, albeit with lower treatment levels.

The strategic substitution pattern, i.e., the way treatment by conventional farmers decreases as treatment by organic farmers increases along with the share of organic farming in the landscape, can be characterized by the following derivatives

$$
\frac{d(St^o)}{dS} = \frac{(m+1)\gamma^o + n\gamma^c}{(n+m+1)\gamma^o}, \tag{A2}
$$

$$
\frac{d((1-S)t^c)}{dS} = -\frac{(n+1)\gamma^c + m\gamma^o}{(n+m+1)\gamma^c}. \tag{A3}
$$

First, note that the strategic substitution pattern only depends on the pesticide effectiveness and number of farmers in each group, and not on the relative treatment costs or disease severity. For

$n = m$ and $\gamma^c = \gamma^c = \gamma$, there is a perfect strategic substitution ($\frac{d(St^o)}{dS} = -\frac{d((1-S)t^c)}{dS}$=1), with an overall constant level of total treated area. Reallocating land between farm type does not change the total treatment level (as long as the free-riding thresholds are not reached). Whenever there is an asymmetry, the slopes would differ, making substitution imperfect. For example, if $\gamma^c > \gamma^o$, we obtain $\frac{d(St^o)}{dS} > 1$ and $-1 < \frac{d((1-S)t^c)}{dS}$, making the first slope steeper and the second one flatter. The way the total treated area increases with the share of organic farming is given by $\frac{d(St^o+(1-S)t^c)}{dS} = \frac{(\gamma^c-\gamma^o)(m\gamma^o+n\gamma^c)}{(n+m+1)\gamma^o\gamma^c}$, meaning that total treated area would increase with organic landscape share if $\gamma^c > \gamma^o$. The magnitude of this effect depends on the number of farmers in each group.

# B Data appendix

## B.1 Measurement errors for conventional treatments against FD

A potential issue with our data is that the BNVD does not classify the pesticide purchases by crop and by disease, but only by product. This can lead to measurement errors in our dependent variables if the products used against FD can also be used against other pests/diseases. Fortunately, insecticide products used by organic farmers are measured without errors because there is only one approved product against leafhoppers, *pyrevert*, which has no other significant use in vineyards or on other crops (all of their purchases are thus assumed to be applied against the FD vector).

This is not the case for conventional products, which require more complex computations. Our strategy consists of balancing (i) the selection of approved products purchased in postcodes within MCPs that are highly specialized in vineyards (see Section 3.1.2 for the definition of the MCP), and (ii) the deletion of approved products purchased in postcodes without vineyards (inside and outside MCPs). Overall, the insecticide sale data counts 108 approved products against leafhoppers for conventional farmers over the period 2016–2017. We define the specialized postcodes as those where vineyards represent more than 70% of the Utilized Agricultural Area (UAA), excluding permanent grasslands (that do not receive any insecticide applications) – data sources for vineyard and utilized agricultural area are described in Section 3.1.2 of the main text. There are 183 such postcodes within MCPs in France, from which we select the $N$ most-used products (i.e., those for which the quantities purchased can treat the largest vineyard area following the recommended dosages). Our preferred analysis includes $N = 10$ products (i.e., the ten most-used products by farmers within specialized postcodes with MCP; see Section 4). Although we consider only the products that are specifically approved against leafhoppers in vineyards, and then only select the products that are intensively used within highly specialized postcodes included in MCPs, this selection alone may not convincingly eliminate the risk of including irrelevant products. Hence, we investigate whether each product is significantly purchased in postcodes where the share of vineyards in the UAA excluding grasslands is below 0.1%. In these 4,000 postcodes (about two thirds of French postcodes), the purchased products cannot be used against the FD vector because the leafhoppers are specific vineyard disease vectors, so, among the $N$ selected products, we drop those that represent more than $\sigma$% of UAA excluding grasslands. Setting $\sigma = 100$ leads us to consider the top $N$ products in specialized postcodes, regardless of how they are used in postcodes without vines. Our preferred analysis exclude all products that account for more than $\sigma = 0.1\%$ of the UAA (see Section 4). Our considered lists are then parameterized by $N$, thus increasing type I errors and decreasing type II errors, whereas decreasing $\sigma$ does the reverse. In the econometric analyses, we evaluate the salience of this selection of products by considering eight different lists of insecticides to be accounted for in the measurement of out outcome variables for conventional farmers, with respectively $N \in \{10, 15, 20\}$ and $\sigma \in \{0.5, 5, 100\}$.

Figure B1 shows how this strategy plays out for four major wine regions of France. For each most-used insecticide product on the x-axis, the y-axis indicates the ratio between the potential treated area – corresponding to purchased quantities adjusted for ANSES recommended doses – and the total UAA without grassland. The green (resp. red) bar represents specialized postcodes (resp. postcodes without vineyards). For all regions, almost all $N = 20$ most-used products are not significantly used in postcodes without vineyards, and represent a cumulative share of more than 90% of what can be treated with all the 108 approved products. For the Aquitaine region of Figure B1, "*Cythrine max*", "*Lambdastar*", and "*Karateavec*" appear to be significantly purchased in postcodes without vineyards, such that they would be removed for $\sigma < 5\%$ in the robustness analysis.

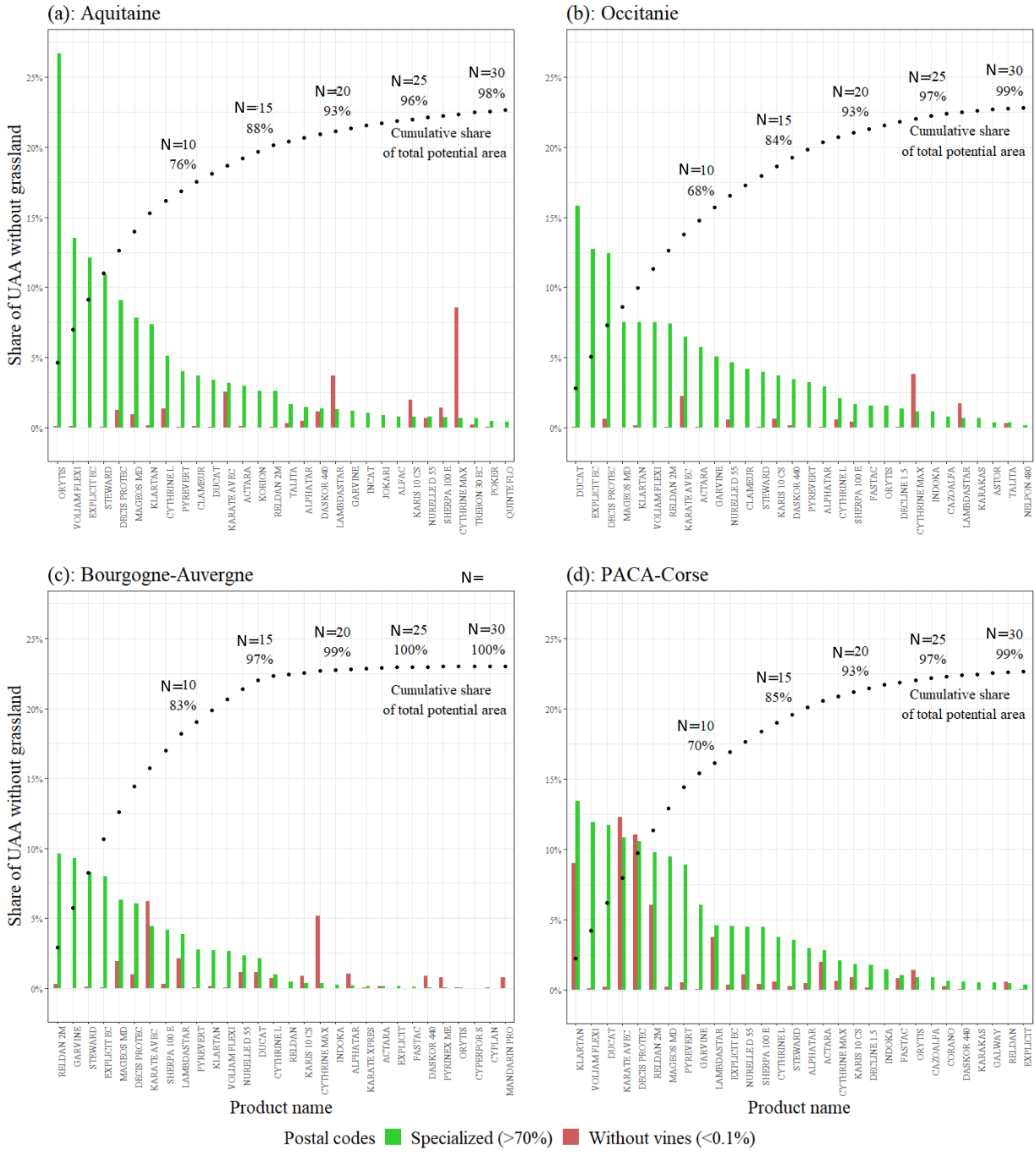


Figure B1: Regional analysis for the restricted lists of insecticide products.

Note. The four panels represent the main wine-producing regions of France. The bars show the share of Usable Agricultural Area (UAA, without grasslands) that could be treated with the observed sales of each insecticide product. We distinguish the specialized postcodes and the postcodes without vineyards, to show that products with other uses can be dropped depending on $t$. The dotted lines represent the cumulative shares of the most-used products for specialized postcodes. The vast majority (>80%) of treatments are applied using the 10 to 15 most-used products, depending on the region.

## B.2 Summary statistics

Table B1 reports the main summary statistics below. They show that the average (total) vineyard area for postcodes with organic vineyards is 807 ha, instead of 83 ha for those without (i.e., postcodes with conventional vineyards only). Hence, the total vineyard area in organic-conventional mixed postcodes is about ten times larger than those in pure conventional postcodes, thus requiring us to weight the postcodes by their corresponding vineyard area in the econometric approach. In total, organic vineyards represents 8% of the total vineyard area (from all 1,228 postcodes with vineyards), but about 15% in the 783 organic-conventional mixed postcodes.

Table B1: Summary statistics in 2017

| | **Num. Obs.** | **Weighted Mean** | **Mean** | **S.D.** | **Min** | **Median** | **Max** |
|---|---|---|---|---|---|---|---|
| Treated organic vineyard (%) | 783 | 67.10 | 142.35 | 1,414.62 | 0.00 | 0.00 | 38,774.44 |
| Treated conventional vineyard(%) | 1,228 | 112.00 | 1,511.45 | 11,185.62 | 0.00 | 57.62 | 226,530.60 |
| Organically treated vineyard (%) | 783 | 13.24 | 14.01 | 178.51 | 0.00 | 0.00 | 5,200.41 |
| Conventionally treated vineyard (%) | 1,228 | 103.80 | 1,187.72 | 9,637.94 | 0.00 | 52.67 | 226,530.6 |
| Share of organic vineyards $S$ (%) | 1,228 | 0.08 | 0.10 | 0.16 | 0.00 | 0.03 | 0.99 |
| Vineyard area (ha) | 1,228 | – | 544.54 | 1,003.11 | 0.01 | 124.97 | 9,870.77 |
| MCP (0/1) | 1,228 | – | 0.53 | 0.50 | 0.00 | 1.00 | 1.00 |
| Rainfall (cm) | 1,228 | – | 63.44 | 12.79 | 41.04 | 60.87 | 134.42 |
| Vineyard price (100,000 €/ha) | 1,194 | – | 0.77 | 2.34 | 0.04 | 0.15 | 27.60 |

NOTES. The table displays the summary statistics of our sample for the year 2017. The first two lines indicate the proportion of organic (resp. conventional) vineyard area that is treated against the FD vector (leafhoppers). The third and fourth lines indicate the proportion of *total vineyard area* that is treated with organic (resp. conventional) products. The means reported in the second column are weighted by the vineyard areas. For example, the weighted mean of the share of treated organic (resp. conventional) vineyard is weighted by the organic (resp. conventional) vineyard area of the postcodes. See the main text for a full description of the variables and their corresponding sources.

## B.3 Descriptive maps

Figure B2 shows the spatial distribution of our main variables across our sample in France.

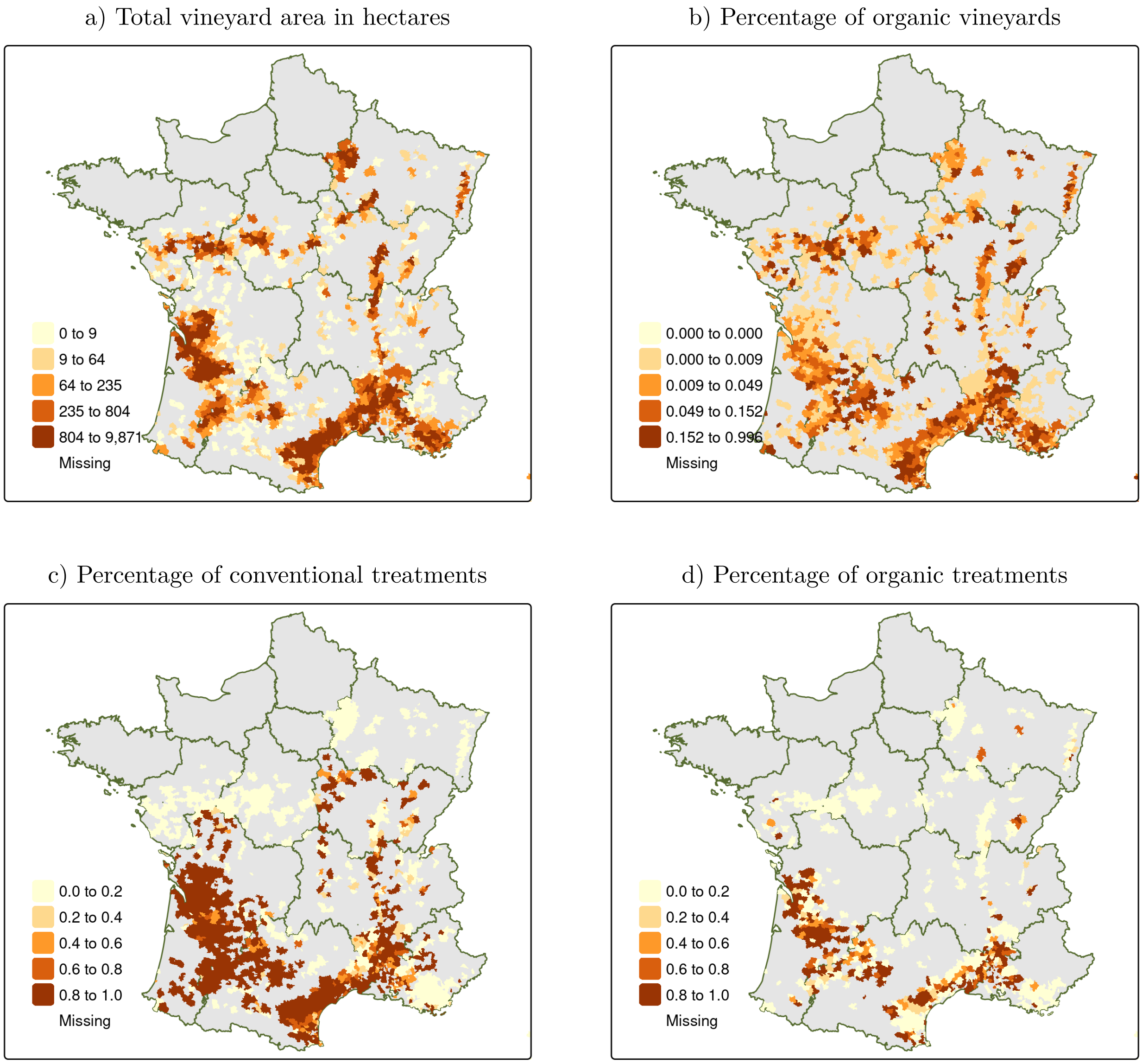


Figure B2: Geographical distribution of principal variables.

NOTE. The figures show the distribution of our main variables over space in our sample (for the postcodes with strictly positive organic vineyard area; i.e., where $S > 0$). Postcodes in light gray are those without vineyards. Panel a. displays the whole total vineyard area per postcode. Panel b. shows the proportion of organic vineyard area out of the total vineyard area (i.e., the organic landscape shares $S$). Panel c. displays the proportion of conventional vineyards treated with conventional treatments $t^c$. Panel d. displays the proportion of organic vineyards treated with organic treatments $t^o$. The area shares of both treatments in panels c. and d. are censored at 100% to increase readability (see Appendix B.2 and the corresponding text in the main manuscript).

# C Econometric appendices

## C.1 Graphical representation of the preferred estimates

Figure C1 displays the graphical representation of the proportion of the landscape that is treated with conventional or organic treatments when the organic landscape share $S$ increases. The green and red solid curves represent the average landscape shares that are respectively treated with organic and conventional treatments, recomputed from our preferred estimates reported in Table 1 of the main text – those with controls in columns (2) and (4). The blue line represents the total treatment, recomputed as a piecewise function of three pieces depending on the free-riding behaviour triggered by $S$ (only conventional farmers treat, both farmers treat, or only organic farmers treat). The 90% confidence intervals are displayed in dashed lines around the average effects, and recomputed with the delta method using the heteroscedasticity-robust standard errors associated with our preferred estimates. The histogram above the curves displays the distribution of the organic landscape shares $S$, showing that most of the postcodes are covered by a small proportion of organic farmers. This low representation of organic farmers explain why the precision of the estimated effects quickly reduce as $S$ tends towards one.

Figure C1 provides a good illustration of the main findings from Section 4.1, where we see that (i) the proportion of the landscape treated by conventional farmers quickly reduces as the organic landscape share increases, from $t^c(0) = 66\%$ to $t^c(S_{max}) = 0\%$ with $S_{max} = 51\%$, while (ii) the proportion of the landscape treated by the organic farmers increases slowly as $S$ increases, from $t^o(S_{min}) = 0\%$ for $S_{min} = 9\%$ to $t^o(1) = 84\%$, for (iii) a total treatment that is statistically constant as $S$ varies. The estimates are precise around the average point ($S = 0.06$) but imprecise as $S$ tends towards one.

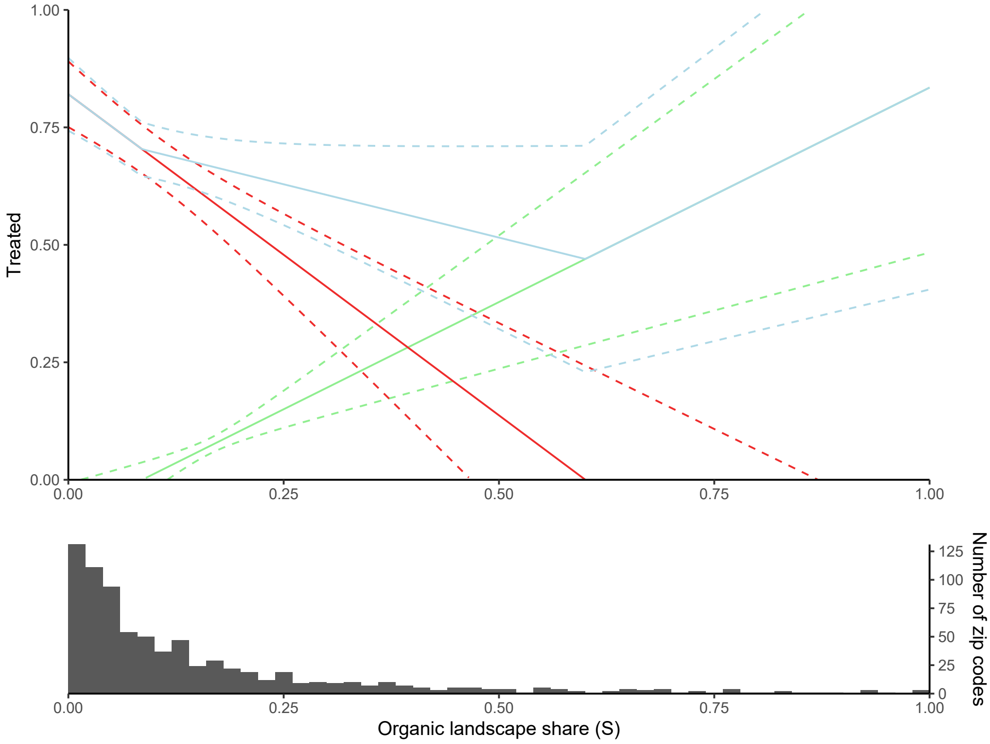


Figure C1: Proportion of organic (green), conventional (red) and total (blue) treated areas.
NOTE. The curves displayed in the Figure represent the evolution of the proportion of the landscape that is treated with either organic or conventional treatment as the organic landscape share ($S$) changes, as predicted by estimates in Table 1 in the main text. The 90% confidence intervals using the heteroscedasticity-robust standard errors are displayed in dashed lines around the average effects (represented by solid lines). The histogram above displays the distribution of the organic landscape shares $S$ in the 873 French postcodes with both conventional and organic vineyards. Because, the estimates are consistent for small variations around the sample mean values (here $S = 0.06$), the precision of the estimated effects quickly reduce as $S$ tends towards one.

## C.2 Sensitivity analysis: linear specification

We change the specification of our dependent variables in equation ((13)) by taking the linear pesticide use instead of the inverse hyperbolic sine transformation. Such specification also permits us to include postcodes with null treatments, but obliges us to work on non-linearized (right-skewed) treatment distributions. Table C1 displays the estimated changes in the share of landscape treated with conventional treatment when the share of organic vineyard $S$ changes, when dropping the inverse hyperbolic sine transformation of the dependent variables, $Y_i^j$. It shows that propositions 1 and 2 are robust to this specification change. Our estimates with controls indicate values for $S_{min}$ and $S_{max}$ of about 10% and 56% respectively.

Table C1: Impacts of $S$ on insecticides used by organic and conventional farmers, with linear transformation of the dependent variable

| | **Organic** | | **Conventional** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constant | -0.104 | -0.128 * | 1.155 *** | 1.214 *** |
| | (0.070) | (0.095) | (0.099) | (0.122) |
| | [0.068] | [0.078] | [0.276] | [0.389] |
| $S$ | 1.262 *** | 1.305 *** | -1.650 | -2.158 * |
| | (0.289) | (0.308) | (0.933) | (0.955) |
| | [0.480] | [0.492] | [1.251] | [1.214] |
| Controls | No | Yes | No | Yes |
| $R^2$ | 0.024 | 0.024 | 0.003 | 0.007 |
| Observations | 783 | 783 | 1,228 | 1,228 |

NOTE. The figures report the estimates of the share of organic vineyards in the vineyard landscape $S$ on insecticides used against FD vectors (leafhoppers) by organic and conventional farmers in 2017 (resp. $Y^o$ and $Y^c$). Estimates in columns (1) and (2) are weighted by the organic vineyard area. Estimates in columns (3) to (6) are weighted by the conventional vineyard area. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using the clustered standard errors.

## C.3 Sensitivity analysis: inclusion of additional conventional pesticides

The dependent variable for conventional farmers contains measurement errors (see Appendix B). To test the sensitivity of our results to these potential errors, we include more conventional insecticides that are (more marginally) used against leafhoppers – but whose inclusion may change our conclusions. Tables C2 to C4 display the results from estimations of equation ((13)) with conventional treatments including the 10 to 20 insecticides most used against FD vectors, with varying cutoff values of $\sigma$ (instead of $N = 10$ and $\sigma = 0.5\%$ in Table 1). These tables indicate that Propositions 1 and 2 hold when including the 10 to 20 most-used insecticides, but only significantly when controls are added. In any case, no result from C2 to C4 rejects these propositions. Overall, our estimates with controls from Tables C2 to C4 suggest estimated values of $S_{max}$ comprised between about 60% to 75% when using the models with controls (in line with our preferred analyses).

Table C2: Impacts of $S$ on insecticides used by conventional farmers depending on the number of conventional pesticides included (N=10)

| | **Conventional $\sigma$=0.5%** | | **Conventional $\sigma$=5%** | | **Conventional $\sigma$=100%** | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Constant | 0.835 ***<br>(0.022)<br>[0.180] | 0.770 ***<br>(0.027)<br>[0.226] | 0.978 ***<br>(0.025)<br>[0.194] | 0.966 ***<br>(0.030)<br>[0.254] | 1.036 ***<br>(0.026)<br>[0.168] | 1.066 ***<br>(0.031)<br>[0.218] |
| $S$ | -1.140<br>(0.206)<br>[0.694] | -1.367 **<br>(0.207)<br>[0.651] | -1.106<br>(0.239)<br>[0.684] | 1.525 **<br>(0.238)<br>[0.617] | -0.876<br>(0.247)<br>[0.611] | -1.456 **<br>(0.241)<br>[0.566] |
| Controls | No | Yes | No | Yes | No | Yes |
| $R^2$ 0.024 | 0.067 | 0.017 | 0.072 | 0.010 | 0.099 | |
| Observations 1,228 | 1,228 | 1,228 | 1,228 | 1,228 | 1,228 | |

Note. The figures report the estimates of the share of organic vineyards in the vineyard landscape $S$ on the inverse hyperbolic sine transformation on pesticide purchases of conventional farmers in 2017 ($Y^C$), for different sets of conventional pesticides considered. Estimates in columns (1) to (12) are weighted by the conventional vineyard area. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using the clustered standard errors.

Table C3: Impacts of $S$ on insecticides used by conventional farmers depending on the number of conventional pesticides included (N=15)

| | **Conventional $\sigma$=0.5%** | | **Conventional $\sigma$=5%** | | **Conventional $\sigma$=100%** | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Constant | 0.915 *** | 0.857 *** | 1.099 *** | 1.086 *** | 1.153 *** | 1.181 *** |
| | (0.024) | (0.029) | (0.028) | (0.033) | (0.028) | (0.034) |
| | [0.195] | [0.249] | [0.214] | [0.276] | [0.189] | [0.245] |
| $S$ | -1.141 | -1.417 * | -1.256 | -1.727 ** | -1.018 | -1.631 ** |
| | (0.228) | (0.229) | (0.261) | (0.260) | (0.268) | (0.263) |
| | [0.797] | [0.729] | [0.847] | [0.781] | [0.768] | [0.732] |
| Controls | No | Yes | No | Yes | No | Yes |
| $R^2$ | 0.020 | 0.061 | 0.018 | 0.075 | 0.012 | 0.096 |
| Observations 1,228 | 1,228 | 1,228 | 1,228 | 1,228 | 1,228 | |

NOTE. The figures report the estimates of the share of organic vineyards in the vineyard landscape $S$ on the inverse hyperbolic sine transformation on pesticide purchases of conventional farmers in 2017 ($Y^C$), for different sets of conventional pesticides considered. Estimates in columns (1) to (12) are weighted by the conventional vineyard area. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using the clustered standard errors.

Table C4: Impacts of $S$ on insecticides used by conventional farmers depending on the number of conventional pesticides included (N=20)

| | **Conventional $\sigma$=0.5%** | | **Conventional $\sigma$=5%** | | **Conventional $\sigma$=100%** | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Constant | 0.951 *** | 0.899 *** | 1.181 *** | 1.179 *** | 1.240 *** | 1.278 *** |
| | (0.025) | (0.030) | (0.030) | (0.036) | (0.031) | (0.037) |
| | [0.202] | [0.261] | [0.233] | [0.301] | [0.206] | [0.269] |
| $S$ | -1.164 | -1.472 ** | -1.329 | -1.837 ** | -1.049 | -1.701 ** |
| | (0.237) | (0.238) | (0.284) | (0.284) | (0.290) | (0.286) |
| | [0.814] | [0.742] | [0.959] | [0.889] | [0.859] | [0.828] |
| Controls | No | Yes | No | Yes | No | Yes |
| $R^2$ | 0.019 | 0.061 | 0.018 | 0.072 | 0.011 | 0.091 |
| Observations 1,228 | 1,228 | 1,228 | 1,228 | 1,228 | 1,228 | |

NOTE. The figures report the estimates of the share of organic vineyards in the vineyard landscape $S$ on the inverse hyperbolic sine transformation on pesticide purchases of conventional farmers in 2017 ($Y^C$), for different sets of conventional pesticides considered. Estimates in columns (1) to (12) are weighted by the conventional vineyard area. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using the clustered standard errors.

### C.4 Sensitivity analysis: extension to the $n + m$ case

Our preferred analyses map the treatment decisions of organic and conventional farmers in the $1+1$ case, that is, as if there were only one organic and one conventional farmer. Yet, in the real world, there could be numerous farmers of each type sharing the landscape (that is, in any postcode). As explored in the theoretical Appendix A.3, the number of organic farmers $n$ and conventional farmers $m$ affect the extent of treatments since $n > 1$ or $m > 1$, by triggering free-riding behaviour. One question that naturally arises in these conditions is whether the strategic interactions identified in our preferred analyses remain when we move from the $1 + 1$ to the $n + m$ case.

To test for this possibility, we add the number of organic and conventional winegrowers in each postcode. The organic winegrowers were sourced from the detailed historical records available on the French government's open data platform (https://www.data.gouv.fr/fr/datasets/historique-detaille-des-surfaces-cheptels-et-nombre-doperateurs-par-commune/). Conventional winegrowers were derived from coupling this previous information with the 2020 Agricultural Census, with a random assignment of operator counts for postcodes where the number of operators was less than 30 but known to be greater than zero (from a uniform distribution between 1 and 30). This adjustment was necessary to retain all the postcodes from our initial database, but could lead to measurement errors in the less specialized postcodes.

Table C5 displays the responses of organic and conventional farmers when the share of organic vineyard $S$ changes, conditionally on the number of conventional and organic farmers. Table C5 shows that all the elements of proposition 1 and 2 hold when looking at these figures. In other words, we still identify the substitution pattern between conventional and organic farmers as $S$ increases, even when we control for the number of farmers of each type in the estimations. That is, the strategic interactions between groups remain even after having controlled for those occurring within each group.[C1] We notably consistently identify free-riding areas characterized by $S_{min} = 9\%$ and $S_{max} = 59\%$, in line with our preferred analyses.

[C1] Note on this aspect that, as theoretically predicted, the number of farmers within each group reduced the treatments within the group (at least for conventional farmers).

Table C5: Impacts of $S$ on insecticides used by organic and conventional farmers conditionally on the number of farmers of each type

| | **Organic** | | **Conventional** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constant | -0.074 * | -0.085 *** | 0.875 *** | 0.800 *** |
| | (0.014) | (0.015) | (0.026) | (0.026) |
| | [0.047] | [0.038] | [0.200] | [0.205] |
| $S$ | 0.887 ** | 0.901 *** | -1.152 * | -1.346 *** |
| | (0.047) | (0.048) | (0.208) | (0.203) |
| | [0.289] | [0.284] | [0.654] | [0.481] |
| $n$ | 0.009 | 0.008 | -0.004 | -0.019 *** |
| | (0.003) | (0.003) | (0.008) | (0.008) |
| | [0.009] | [0.010] | [0.009] | [0.007] |
| $m$ | 0.000 | -0.000 | -0.000 | -0.001 ** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| | [0.000] | [0.000] | [0.001] | [0.000] |
| Controls | No | Yes | No | Yes |
| $R^2$ | 0.334 | 0.340 | 0.032 | 0.116 |
| Observations | 783 | 783 | 1,228 | 1,228 |

Note. The figures report the estimates of the share of organic vineyards in the vineyard landscape $S$ on the inverse hyperbolic sine transformation on pesticide purchases of organic and conventional farmers in 2017 (resp. $Y^O$ and $Y^C$). Estimates in columns (1) and (2) are weighted by the organic vineyard area. Estimates in columns (3) to (6) are weighted by the conventional vineyard area. The estimations extend our preferred ones by including the number of organic winegrowers ($n$) and conventional winegrowers ($m$) in the postcode, centered around the mean of the sample. Additional controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using the clustered standard errors.

## C.5 Sensitivity analysis: year 2016

Table C6 displays the estimated changes in the share of landscape treated with organic and conventional treatments in 2016 (instead of 2017) when the share of organic vineyard $S$ changes. It shows that all elements of propositions 1 and 2 hold when taking the year 2016 instead of the year 2017. Our preferred estimates with controls indicate values for $S_{min}$ and $S_{max}$ of about 7% and 58% respectively. Compared to our results in Section 4.1, this means that we identify a larger extent of $S$ values for which organic and conventional farmers' contributions compensate one for another. As depicted in Section 4.1, results from Table C6 show that the organic farmers *only compensate to a partial extent* for the reduction in conventional farmers' treated area as $S$ increases (by a factor of about 0.6 here).

Table C6: Impacts of $S$ on insecticides used by organic and conventional farmers in 2016

| | **Organic** | | **Conventional** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constant | -0.031 | -0.050 ** | 0.829 *** | 0.746 *** |
| | (0.010) | (0.014) | (0.022) | (0.026) |
| | [0.031] | [0.025] | [0.193] | [0.233] |
| $S$ | 0.742 *** | 0.768 *** | -1.096 | -1.286 ** |
| | (0.043) | (0.046) | (0.203) | (0.204) |
| | [0.208] | [0.191] | [0.687] | [0.633] |
| Controls | No | Yes | No | Yes |
| $R^2$ | 0.277 | 0.285 | 0.023 | 0.070 |
| Observations | 783 | 783 | 1,228 | 1,228 |

NOTE. The figures report the estimates of the share of organic vineyards in the vineyard landscape $S$ on the inverse hyperbolic sine transformation on pesticide purchases of organic and conventional farmers in 2016 (resp. $Y^O$ and $Y^C$). Estimates in columns (1) and (2) are weighted by the organic vineyard area. Estimates in columns (3) to (6) are weighted by the conventional vineyard area. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using the clustered standard errors.

## C.6 Sensitivity analysis: extensive margin response

While our preferred results examined the aggregated farmers' pesticide use responses, we check here whether $S$ explains the very decision to apply insecticides against leafhoppers (binary variable taking the value one when farmers apply insecticides against the FD vectors, zero otherwise). That is, we examine whether we can identify strategic interactions by looking at the farmers' *extensive margin* decisions (instead of their *total* use). We note this binary decision $\tilde{Y}^j = 1$ if $Y^j > 0$ and $\tilde{Y}^j = 0$ if $Y^j = 0$. Table C7 displays the responses of organic and conventional farmers at the extensive margin when the share of organic vineyard $S$ changes. It shows that all the elements of Proposition 1 hold when looking at the extensive margin responses. Organic farmers are less likely to free-ride when $S$ increases.

Table C7: Impacts of $S$ on organic and conventional farmers' binary decision to use insecticides

| | **Organic** | | **Conventional** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constant | 0.712 *** | 0.461 *** | 0.834 *** | 0.738 *** |
| | (0.026) | (0.032) | (0.070) | (0.017) |
| | [0.060] | [0.070] | [0.118] | [0.148] |
| $S$ | -0.055 | 0.323 *** | -0.041 | -0.162 |
| | (0.106) | (0.104) | (0.136) | (0.134) |
| | [0.124] | [0.102] | [0.302] | [0.286] |
| Controls | No | Yes | No | Yes |
| $R^2$ | 0.000 | 0.171 | 0.000 | 0.073 |
| Observations | 783 | 783 | 1,228 | 1,228 |

NOTE. The figures report the estimates of the share of organic vineyards in the vineyard landscape $S$ on the binary decision to purchase pesticides for organic and conventional farmers in 2017 ($\tilde{Y}^j = \{0, 1\}$, for $j \in \{o; c\}$). Estimates in columns (1) and (2) are weighted by the organic vineyard area. Estimates in columns (3) and (4) are weighted by the conventional vineyard area. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using the clustered standard errors.

## C.7 Sensitivity analysis: intensive margin response

We examine here whether $S$ explains the farmers' intensive margin responses to apply pesticides – that is, conditional on the positive (binary) decision of applying pesticides (see above), whether $S$ positively (resp. negatively) affects organic (resp. conventional) treatments against leafhoppers, as predicted in proposition 2. These intensive margin responses respectively correspond to $Y^o$ and $Y^c$, for those that purchase pesticides ($\tilde{Y}^o = 1$ and $\tilde{Y}^c = 1$ respectively). That is, conditionally on the positive decision to treat against FD, what is the share of treated vineyards in the landscape. Table C8 displays the responses of organic and conventional farmers at the intensive margin when the share of organic vineyards $S$ changes. It shows that all the elements of proposition 2 hold when looking at the intensive margin. In other words, we still identify the substitution pattern between conventional and organic farmers as $S$ increases.

Table C8: Impacts of $S$ on intensive decision to use insecticides by organic and conventional farmers

| | **Organic** | | **Conventional** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constant | -0.083 ** | -0.087 *** | 1.004 *** | 1.008 *** |
| | (0.015) | (0.023) | (0.024) | (0.030) |
| | [0.039] | [0.040] | [0.113] | [0.169] |
| $S$ | 1.275 *** | 1.291 *** | -1.383 ** | -1.546 *** |
| | (0.064) | (0.069) | (0.226) | (0.232) |
| | [0.232] | [0.236] | [0.603] | [0.575] |
| Controls | No | Yes | No | Yes |
| $R^2$ | 0.530 | 0.533 | 0.044 | 0.053 |
| Observations | 352 | 352 | 823 | 823 |

NOTE. The figures report the estimates of the share of organic vineyards in the vineyard landscape $S$ on the inverse hyperbolic sine transformation of pesticide purchases of organic and conventional farmers *purchasing pesticides* in 2017 ($Y^j|\tilde{Y}^j = 1$ for $j \in \{C; O\}$). Estimates in columns (1) and (2) are weighted by the organic vineyard area. Estimates in columns (3) and (4) are weighted by the conventional vineyard area. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using the clustered standard errors.

### C.8 Sensitivity analysis: pesticide intensity

Our last sensitivity analysis consists of explaining pesticide intensity, $t^j$, instead of aggregated pesticide use (i.e., $Y^j$). That is, we examine whether we can identify strategic interactions by looking at the proportion of organic and conventional vineyards that are treated, instead of the total landscape share treated. Table C9 displays the responses of organic and conventional farmers in terms of pesticide intensity when the share of organic vineyard $S$ changes. Tables C10 and C11 break down these effects at the extensive and intensive margin respectively. These pesticide intensities respectively correspond to $t^o$ and $t^c$ in Section 2.[C2] Table C9 shows that all the elements of proposition 2 hold significantly with unclustered standard errors (but not when the latter are clustered). In other words, we still identify the substitution pattern between conventional and organic farmers as $S$ increases. However, the elements of proposition 1 are not always empirically verified in this sensitivity analysis. Proposition 1only hold on conventional farmers when including additional controls (see column (4) of Table C9). This implies that, if we can identify some free-riding behaviour for conventional farmers when looking at marginal contributions (with associated $S_{max} \approx 98\%$), we cannot identify such behaviour for organic farmers (or, in other words, $S_{min} = 0\%$). Table C10 shows that we can however identify such effects when looking at the extensive margin responses of $t^j$ only. Finally, Table C11 shows that proposition 2 significantly holds when looking at the intensive margin responses of $t^j$ only (with unclustered standard errors).

[C2] They represent the share of organic (resp. conventional) vineyard that is treated by organic (resp. conventional) treatment, and thus differ from our preferred dependent variable $Y^O$ and $Y^C$ (which represent the share of vineyard treated by organic and conventional treatment respectively).

Table C9: Impacts of $S$ on the intensity of insecticides used by organic and conventional farmers

| | **Organic** | | **Conventional** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constant | 0.435 *** | 0.295 *** | 0.831 *** | 0.762 *** |
| | (0.032) | (0.042) | (0.023) | (0.028) |
| | [0.113] | [0.110] | [0.182] | [0.229] |
| $S$ | 0.176 | 0.387 | -0.533 | -0.780 |
| | (0.131) | (0.137) | (0.215) | (0.215) |
| | [0.410] | [0.334] | [0.707] | [0.658] |
| Controls | No | Yes | No | Yes |
| $R^2$ | 0.002 | 0.037 | 0.005 | 0.052 |
| Observations | 783 | 783 | 1,228 | 1,228 |

Note. The figures report the estimates of the share of organic vineyards in the vineyard landscape $S$ on the inverse hyperbolic sine transformation on pesticide intensity used by organic and conventional farmers in 2017 (resp. $t^o$ and $t^c$). Estimates in columns (1) and (2) are weighted by the organic vineyard area. Estimates in columns (3) to (6) are weighted by the conventional vineyard area. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using the clustered standard errors.

Table C10: Impacts of $S$ on the intensity of insecticides used by organic and conventional farmers – extensive margin responses

| | **Organic** | | **Conventional** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constant | 0.712 *** | 0.461 *** | 0.834 *** | 0.738 *** |
| | (0.026) | (0.032) | (0.070) | (0.017) |
| | [0.060] | [0.070] | [0.118] | [0.148] |
| $S$ | -0.055 | 0.323 *** | -0.041 | -0.162 |
| | (0.106) | (0.104) | (0.136) | (0.134) |
| | [0.124] | [0.102] | [0.302] | [0.286] |
| Controls | No | Yes | No | Yes |
| $R^2$ | 0.000 | 0.171 | 0.000 | 0.073 |
| Observations | 783 | 783 | 1,228 | 1,228 |

Note. The figures report the estimates of the share of organic vineyards in the vineyard landscape $S$ on the binary decision to purchase pesticides for organic and conventional farmers in 2017 ($\tilde{t}^j = \{0, 1\}$ for $j \in \{o; c\}$). Estimates in columns (1) and (2) are weighted by the organic vineyard area. Estimates in columns (3) to (6) are weighted by the conventional vineyard area. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using the clustered standard errors.

Table C11: Impacts of $S$ on the intensity of insecticides used by organic and conventional farmers – intensive margin responses

| | **Organic** | | **Conventional** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constant | 0.609 *** | 0.651 *** | 0.998 *** | 0.999 *** |
| | (0.048) | (0.070) | (0.025) | (0.031) |
| | [0.118] | [0.115] | [0.115] | [0.173] |
| $S$ | 0.312 | 0.255 | -0.619 | -0.792 |
| | (0.199) | (0.214) | (0.234) | (0.240) |
| | [0.398] | [0.362] | [0.623] | [0.590] |
| Controls | No | Yes | No | Yes |
| $R^2$ | 0.007 | 0.009 | 0.008 | 0.019 |
| Observations | 352 | 352 | 823 | 823 |

NOTE. The figures report the estimates of the share of organic vineyards in the vineyard landscape $S$ on the inverse hyperbolic sine transformation of pesticide intensity of organic and conventional farmers *purchasing pesticides* in 2017 ($t^j|\tilde{t}^j = 1$ for $j \in \{o, c\}$). Estimates in columns (1) and (2) are weighted by the organic vineyard area. Estimates in columns (3) and (4) are weighted by the conventional vineyard area. Controls include total vineyard area and other permanent crop area in the postcode, centered around the sample mean. In addition to reporting heteroscedasticity-robust standard errors in ordinary brackets, we report clustered standard errors at the NUTS2 regional level in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 using the clustered standard errors.