Title: Disease dispersion as a spatial interaction: The case of *Flavescence Dorée*

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Abstract

Flavescence dorée is a serious and incurable vine disease transmitted by an insect vector. Focusing on its spatial diffusion and on its control with pesticides, this paper investigates the private strategies of wine producers and their socially optimal counterparts. The socially optimal regulation has to address two externalities regarding private treatment decisions: i) the insufficient consideration of collective benefits from controlling the vector populations; ii) the failure to take into account environmental damage related to pesticide application. The probability of infection is estimated on French data from a spatial econometric specification. Three alternative assumptions are examined regarding producers' anticipation of the impact of their own treatment: naive, myopic or farseeing, in increasing order of sophistication. Because of the two dimensions of externalities, no type of anticipation leads to a systematically preferable situation and optimal policy intervention requires a tax for environmental externalities and a subvention for protection externalities.

Recommendations for Resource Managers:

- Current policy of compulsory treatment is justified by the positive protection externalities.
- This policy is particularly appropriated if producers' anticipations are naive or myopic.
- Taking into account negative externalities decreases the case for compulsory treatment.
- With two externalities, sophisticated anticipations are not necessary closer to the optimum.

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1 Introduction

Flavescence dorée (FD) is an incurable infectious disease that affects European vineyards and causes serious economic damage (Chuche and Thiéry, 2014; Bradshaw et al., 2016). The disease is caused by a phytoplasma transmitted to vine plants by a leafhopper (*Scaphoideus titanus*) that was accidentally introduced from North America. The first observation of FD in Europe dates back to 1955 in Bordeaux vineyards of France (Caudwell, 1957, cited by Chuche and Thiéry, 2014). From the nineties onward, FD has become a serious concern in France as its presence has spread almost throughout the territory, with the first cases reported in the Burgundy vineyards in 2011 and regularly threatening the Champagne vineyards. The disease is now present in large portions of Southern Europe from Portugal to Serbia and is already established in the main grape-growing EU countries (Jeger et al., 2016).

Because there is no cure for FD once a vine plant is infected, current regulations focus on containing its spread by (1) vineyard surveillance, (2) uprooting contaminated plants and (3) insecticide application targeted on the insect vector. More precisely, the French regulation against FD proceeds as follows. If FD symptom is found on one vine plant and the diagnosis is confirmed by laboratory analysis, infected vine plant has to be removed without compensation. Then, the corresponding *commune* (i.e., municipality) and the adjacent *communes* are decreed in Mandatory Control Perimeter (MCP). Within MCP areas, surveillance is supervised by a dedicated organization and insecticide treatments must be applied by all winegrowers two or three times a year, according to the reproductive cycle of the vector insect. From 2013 to 2016, the vineyard acreages under MCP have increased by 25.5% in France. In 2016, more than 556,000 hectares were under MCP, about 73% of the whole vineyard.

At first glance, the management of the FD disease is a textbook case of a treatment externality, where individuals do not take into account the positive collective consequences of their choices and under-provide vector regulation. Accordingly, mandatory treatment appears as an operational, although heuristic, solution to internalize the social benefit of treatment applications. However, several features make this problems more complex than a typical under-provision of a public good issue. First, there is a second externality problem linked to the environmental toxicity of insecticide treatments, which may interfere with the objective of controlling the vector and could reverse the argument of insufficient private treatment choices (Sexton et al., 2007). Moreover, the spatial dispersion of the disease combined with the immobility of vineyard plots introduce some local inter-dependencies between decentralized private choices. The probability of being infected by the FD for a given vineyard depends on the contamination of neighboring vineyards and treatment choices made by the neighboring winegrowers. It should be noted that this dependency decreases with distance, hence the MCP part of the current policy against FD uses contiguity between municipalities as an attempt to take into account this spatial dispersion pattern of the disease through its vector.

In particular, we characterize the private incentives of winegrowers to take measures against the FD in the presence of positive externalities from insecticide treatments. We investigate different levels of sophistication in their anticipations regarding the effect of their own treatment decision on their contamination and the contamination of their neighbors. Producers with naive anticipation only consider the direct effect of the treatment on their own plot ; myopic producers anticipate that their treatments also decrease the risk of their first-order neighbors, and therefore the risk that the disease spreads from the neighboring plot to their own ; farseeing producers take into account the induced effects of their own treatment on the whole population (i.e., for higher orders of neighborhood). These different degrees of sophistication are related to different believes about the probability model of FD contamination, its spatial autocorrelation in particular. The under-provision of vector regulation decreases with the sophistication of producers' anticipation, while none of them takes into account the benefits on other producers. The social optimum is not reached in any case and requires additional regulations that we study.

We propose a spatial econometric estimation (LeSage and Pace, 2009) for the probability of FD dispersion inspired from species distribution models typically used to study the dispersion of invasive species (Barbet-Massin et al., 2018). We provide a spatially-explicit characterization of the probability of contamination by FD for the whole France under alternative treatment scenarios, and estimate the private and social costs and benefits from insecticide treatments. From this empirical model, the simulation of private choice according to the different assumption about producers' anticipations, and the simulation of the social optimum allows us to study spatially the inefficiencies of private decisions and to study the effect of a tax on treatment application in order to internalize the negative environmental externality. We characterize a spatial mismatch in the policy, i.e., situations where treatments should be mandatory or conversely, where they should be forbidden because environmental costs outweigh benefits from avoiding pest dispersion. We show that policy recommendations may require to prevent some winegrowers to treat their plot, or conversely to subsidize / make treatments mandatory, depending on the level of the environmental damage.

The paper is structured as follows. The related literature is introduced in section 2. Section 3 presents a stylized model of FD dispersion (3.1) and of producers' choices with regard to pesticide application (3.2). Private and social optima for the general problem with two sources of externalities are then compared (3.3). The empirical model of FD dispersion is presented in section 4, jointly with the estimation methods (4.2), and the cost-benefit framework (4.3). The data are presented in section 5, jointly with the specification of the spatial dependence between producers' choices (5.3). Section 6 discusses the coefficients estimated from econometric models (6.1) and the predicted probabilities of FD contamination according to different anticipation schemes (6.2). Section 7 reports policy simulations with a tax on pesticide application (7.2) and an evaluation of current policy (7.3). Section 8 concludes.

2 Related literature

Several strands of the literature dealing with spatial externalities can be related to our paper. The agricultural economics literature has widely investigated the costs and benefits of pesticide use, with some contributions addressing the trade-off between productivity considerations and environmental health side effects. In their review of existing methodologies, Sexton et al. (2007)

recall that measuring pesticide productivity has been a contentious issue for several decades, and raises modeling issues (yield-increasing input vs. damage-control approach, specification of the damage function, risk considerations). Alston et al. (2013) develop a simulation of the wine-grape industry to evaluate the costs and benefits of a program aimed at controlling the dissemination of the Pierce's disease in California. This disease shares characteristics with FD as it is an incurable insect-transmitted disease of the vineyards. Their evaluation for the program considers not only application costs for pesticides and avoided losses to winegrowers (modeled as a destruction of productive capital), but also the upstream nursery industry and the demand side (through an estimation of its price elasticity). Without taking into account the environmental cost of pesticides, their evaluation of avoided losses permitted by the program is found to far exceeds its costs.

Brown et al. (2002) propose a conceptual framework addressing several steps where human decisions can influence the diffusion of insect-transmitted plant diseases. Fuller et al. (2011, 2017) use a spatial-dynamic model of heterogeneous landowners managing a vector-borne disease in a perennial crop, where vines are capital stocks that take time to reach bearing age (i.e. cannot be immediately replaced when diseased). They model disease dispersion and vector control decision made at the vineyard level in the Napa Valley. They focus on the temporal dimension of the question, to show some significant dynamic gains that could be reached from cooperation. They suggest that understanding the spatial dynamics of individual decisions would be important, without explicitly taking them into account. Our paper contributes to this literature by proposing an original spatial econometric estimation of the benefits of insecticide treatments against the vector of FD in France, by investigating the socially optimal parts of vineyard that should be treated as a function of the environmental cost of pesticides, and by providing a first empirical evaluation of the mandatory regulatory scheme.

The broader literature addressing the control of the spatial diffusion of diseases or pest species among farms has recently put a new emphasis on decentralized control and focused on the private incentives of individual, heterogeneous, property managers to take measures. Fenichel et al. (2014) highlight the key role of the property value, and find that higher rates of dispersion, associated with the proximity of neighboring properties, reduce the private incentives for control. Taxes on the level of pest species are shown to have adverse effects by undermining existing incentives generated by property, both at the intensive margin (less spraying) and extensive margin (abandonment of production). Reeling and Horan (2014), focusing on the dispersion of an infectious livestock disease in a strategic setting (when individual protection efforts are a best response to other's efforts), define the relative endogeneity of risk as the extent to which own efforts are sufficient for self-protection, and discuss the coordination failure that may arise when individual efforts are strategic complements. A behaviorally-dependent indemnity is shown to eliminate the possibility of coordination failure. Costello et al. (2017) use a dynamic analytical model of a mobile public bad to characterize the non-cooperative control decisions of heterogeneous individual landowners. They find that due to the spatial externality, a tragedy of commons emerges under private management. The socially optimal level of control across space is found to always exceed (weakly) the level of control undertaken by private owners ; pest mobility and low control by neighbors result in lower private control. Ambec and Desquilbet (2012) focus on the management of pest resistance to illustrate analitically the trade-off between a command-and control instrument which imposes the localization of resource uses and a market-based instrument which delegates this choice to farmers: they find that the pest mobility and farm heterogeneity in probability of contamination determine the relative efficiency of these instruments. An interesting feature in their 2-period model is the investigation of "myopic farmers" who neglect their own impact of common-pool resources in period 2 : their simulations show that policy prescriptions may change depending on whether farmers are assumed to be myopic or not.

Finally, Grogan and Goodhue (2012) provide an original empirical examination of spatial externalities from pesticide use by studying the case where insecticide treatments on a target species in one crop causes unintended damages to species beneficial to another crop. While strategic considerations are not the question addressed in this paper, we contribute to the understanding of the effects of individual incentives for controlling pest dispersion by introducing various degrees of sophistication in anticipations of the effects of the treatment choices, their implications for optimal policies, and a cost-benefit analysis of the current policy. The main originality of our paper is to provide a theoretical framework that supports a spatial econometric analysis of the management of a "public bad". While strategic considerations are not the question addressed, we contribute to the understanding of the effects of individual incentives for controlling pest dispersion by introducing various degrees of sophistication in anticipations of the effects of the treatment choices, their implications for optimal policies, and a cost-benefit analysis of the current policy.

3 Theoretical model

3.1 Disease's dispersion

We model the dispersion of the FD disease through a continuous random variable y^* indicating the contamination level of vineyards. For a given vineyard plot i, the contamination level y_i^* depends additively on an unknown function (the niche) of its biophysical characteristics X_i (e.g., climate, wind, elevation), on the share t_i of its area which is treated with insecticides against the FD vector, on average contamination levels of neighboring plots $\tilde{y}_i^*$, on average share of treated plots $\tilde{t}_i$ in the neighborhood, and on a random term ε_i (the accidental contamination) according to:

$$y_i^* = b(X_i; \boldsymbol{\beta}) + \tau t_i + \rho \tilde{y}_i^* + \theta \tilde{t}_i + \varepsilon_i. \tag{1}$$

The coefficients $\boldsymbol{\beta}$, τ, ρ and θ represent the effects of the different determinants of FD contamination. Depending on the biophysical conditions and on any accidental random event, the term $b(X_i; \boldsymbol{\beta}) + \varepsilon_i$ represents the contamination level in the absence of own treatment, of any treatment and any infection in the neighborhood. This term is neither under the control of the winegrowers nor of public policies. The manager of plot i could decrease the contamination level by increasing the treatment against the vector t_i as τ is expected to be negative (otherwise, the treatment would not have any economic interest). The contamination level is also influenced by treatment choices and contamination levels in the neighborhood of i, through θ and ρ respectively expected to be negative and positive. We note N_i the set of winegrowers in the neighborhood of the vineyard plot i, this set is assumed to be of a given size n (this assumption will be relaxed in the empirical part). Accordingly, $\tilde{t}_i = n^{-1} \sum_{j \in N_i} t_j$ and $\tilde{y}_i^* = n^{-1} \sum_{j \in N_i} y_j^*$. To cancel the reflexive problem inherent to any network with additive errors (Manski, 1993), we consider that the plot i is not in its own neighborhood: $i \notin N_i$.

The contamination levels y_i^* is a latent variable without measurement units that is converted to probability of contamination through a threshold-crossing condition. The vineyard i under consideration is expected to be contaminated by FD once its contamination level reaches a threshold, set to zero without loss of generality. If the random term follows a uniform distribution on [0, 1], the probability of FD contamination is:[1]

$$p_i \equiv \text{Prob}(y_i^* > 0) = b(X_i; \boldsymbol{\beta}) + \tau t_i + \rho \tilde{y}_i^* + \theta \tilde{t}_i \tag{2}$$

This structure of FD dispersion makes all vineyards spatially interdependent both in terms of treatments choices and contamination levels. Any random event for a given plot $j \in N_i$ impacts p_i through the contamination level in the neighborhood $\tilde{y}_i^*$. Any random event that affects another vineyard plot k that is not in the neighborhood of i ($k \notin N_i$) also impacts p_i if this vineyard is in the neighborhood of j (i.e., $k \in N_j$). This is because $\tilde{y}_j^*$ impacts y_i^* through y_j^* that recursively impacts all vineyards with decreasing importance if $\rho < 1$. The same interdependence is true for treatment choices of i that impact directly the contamination levels of first-order neighbors[2] through $\tilde{t}_j$ and indirectly the second-order neighbors and more through $\tilde{y}_j^*$. This static structure of spatial dependence can be justified as the long run stationary equilibrium of a spatio-temporal model of contamination (LeSage and Pace, 2009, Chapter 2, p.25-27).

[1] Assuming a uniform distribution for the random terms corresponds to a linearization of the unknown cumulative distribution function. However, this linearization requires to constrain the probability to be between 0 and 1 in order to derive the theoretical results. In the empirical application, we assume a standard Gaussian distribution, which leads to a standard probit model without the *ad hoc* constraint on the probability.

[2] First-order neighbors are plots that share a border, second-order neigbors are plots that share a border with first-order neighbors, and so on for higher orders. This terminology allows to decompose the spatial dependence between decision units.

The spatial dependence between vineyards for the dispersion of the FD disease is best illustrated by the marginal effect of an increase in the treatment applied by the manager of the vineyard plot i on its own probability of contamination, when the treatments on all other vineyards are fixed. The endogenous contamination level results in a second term in the equation below:

$$\frac{\partial p_i}{\partial t_i} = \tau + n^{-1}\rho \sum\nolimits_{j\in N_i} \frac{\partial y_j^*}{\partial t_i}. \tag{3}$$

Accordingly, the marginal effect for winegrower i of an increase in the treatment applied to its plot is the sum of an own effect through τ and a auto-correlated effect from the decreased contamination levels of neighbors. For a given neighbor $j \in N_i$, this feedback effect can be developed (n is also the number of neighbor of j):

$$\frac{\partial y_j^*}{\partial t_i} = n^{-1}\left[\theta + \rho \sum\nolimits_{k\in N_j} \frac{\partial y_k^*}{\partial t_i}\right]. \tag{4}$$

This shows the spatial dependence as the sum of a first-order spillover effect of the treatment of i on its neighbors through θ and a second-order recursive effect through the contamination of the vineyards k in the neighborhood of j. By substitution, we obtain the marginal effect of the treatment of i as the sum of an own effect, a first-order neighborhood effect and a last term that gathers the higher order effects that are not developed and noted Ψ_j:

$$\frac{\partial p_i}{\partial t_i} = \tau + (\rho/n)\theta + (\rho/n)^2 \sum\nolimits_{j\in N_i} \sum\nolimits_{k\in N_j} \frac{\partial y_k^*}{\partial t_i} \equiv \tau + (\rho/n)\theta + (\rho/n)^2 \sum\nolimits_{j\in N_i} \Psi_j. \tag{5}$$

Note that the order of the spatial effects in Equation 5 can be identified by the exponent put on (ρ/n). Ψ_j corresponds to the spatial effects of order two and more, that will be developed explicitly in the empirical model through matrix notations. The recursive structure of spatial dependence (spatial auto-correlation) implies that the effects concern all plots with at least one neighboring connection with i. If the area of interest does not have any island (separated from the other plots) all the vineyard plots are dependent. The term Ψ_j is expected to be negative as the treatment has a negative effect on contamination levels that are positively spatially auto-correlated. The derivative displayed in Equation 5 is expected to be negative according to the intuitions about the signs of coefficients.

3.2 Private equilibrium

3.2.1 Profit-maximizing treatment choices

With the probability of FD dispersion presented above, we turn to the micro-economic program of a risk neutral winegrower facing the risk of having its vineyard contaminated. Without the disease, the vineyard plot i of a normalized size yields an exogenous annualized gross revenue of r_i. Because the FD disease is incurable, a contamination puts this revenue to zero for some period taken as the planning period.

Given the endogenous risk p_i of being contaminated, the producer is assumed to maximize expected profit with respect to t_i, the share of its vineyard plot that is treated against the FD vector. For simplicity, we assume that producer choices are static and we note c the constant and uniform marginal cost of treatment that is paid and applied before the producer gets the information about contamination. This leads to the following maximization program:

$$\max_{t_i \in [0,1]} \left\{ \mathbb{E}[\pi_i] \equiv (1 - p_i) r_i - c \cdot t_i \right\} \tag{6}$$

The marginal increase in expected revenue from increasing the treatment share is equal to the product $-\partial p_i / \partial t_i \times r_i > 0$ for a marginal cost of $c > 0$. If the marginal revenue is equal to the marginal cost of the treatment, the optimal share of treated area is undetermined, as the producer is indifferent between all values of $t_i \in [0, 1]$. We do not analyze this particular case any further in what follows. Conversely, for all other values of the marginal increase in revenues, the program produces a *bang-bang* decision rule for the optimal treatment choice. The winegrower chooses whether to treat its whole vineyard plot against the vector according to the following trade-off:

$$t_i = \begin{cases} 1 & \text{if } -\partial p_i/\partial t_i > c/r_i \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

This shows that, all other things equal, a higher revenue from wine production increases the probability of treatment, as well as a higher effect of treatment on the probability of infection (i.e., treatment efficiency). The vector of optimal choices for $i \in N$ allows to divide the vineyards into two categories, those that are treated against the FD and the others that are not.

3.2.2 Producers' levels of sophistication in anticipations

We have not detailed the marginal decrease in the probability of contamination that winegrowers anticipate when they make their treatment choices (i.e., $\partial p_i/\partial t_i$). We consider here different assumptions about these anticipations, whether winegrowers take into account only the own effects of the treatment, only the own and first-order spatial effects, or the whole effects described before. While taking into account the effect of one's own treatment on one's own probability of contamination (i.e., τ) seems reasonable, one may question whether winegrowers will take into account the first order effects on their own risk, i.e., the fact that their own treatment also impacts the close neighbors through θ, combined with a auto-correlated effect on their own risk of contamination through ρ. The higher orders are clearly even less likely to be taken into account by winegrowers. Hence, we consider three alternative types of winegrowers with increasing sophistication in anticipated effects of their own treatment choices, and their resulting first-order conditions for profit maximization:

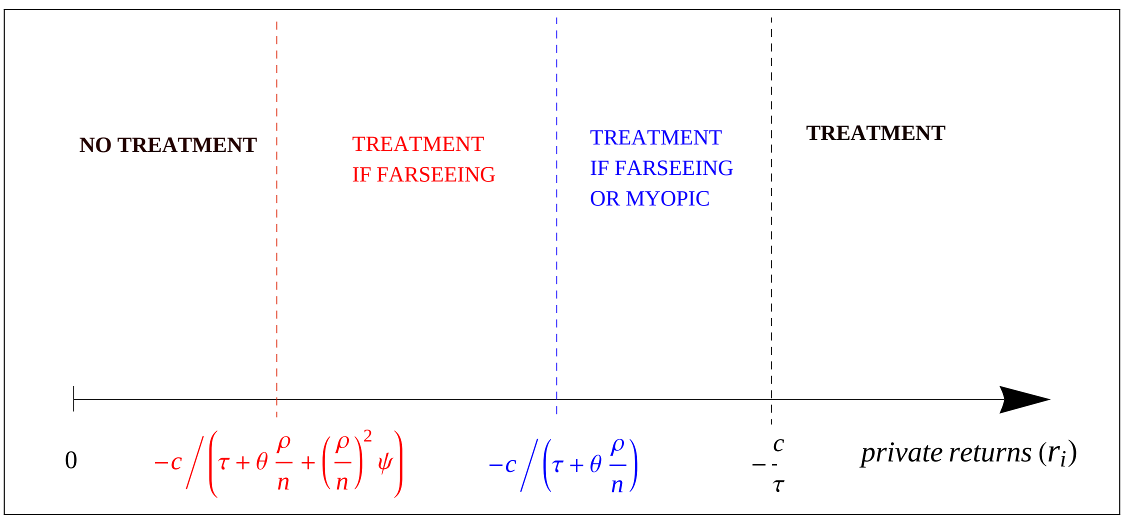
- Naive winegrowers only anticipate the own effects and treat their vineyard iff $r_i > -c/\tau$
- Myopic winegrowers anticipate own and first-order effects, and treat their vineyard iff $r_i > -c/[\tau + (\rho/n)\theta]$.
- Farseeing winegrowers are fully aware of higher-order effects and treat their vineyards iff

$$r_i > -c\left[\tau + (\rho/n)\theta + (\rho/n)^2 \sum_{j\in V_i} \Psi_j\right]^{-1}.$$

These private decision rules are illustrated in Figure 1. For a given revenue r_i, naive winegrowers treat less than the myopic, who treat less than farseeing winegrowers. The consideration of the effects of the treatment on neighbors by sophisticated winegrowers is only driven by individual rationality (profit maximizing behavior), and not by collective considerations, that will be investigated in the next subsection. In the spatial econometric terminology used in the empirical application, the marginal effect of treatment for farseeing winegrowers is called the direct effect of treatment (LeSage and Pace, 2009).

Figure 1: **Winegrower's treatment decision as a function of private returns**

Notes: Treatment choices of winegrowers are determined by their private returns and anticipation types. Treatment choices are increasing with private returns and sophistication of anticipations (from left to right). ψ stands for $\sum_{j\in V_i} \Psi_j$.



3.3 Social optimum

Now consider a social planner seeking to maximize the total expected profit from all vineyard plots $\ell \in N$ simultaneously, with regards to individual treatments t_ℓ. Moreover, because of the environmental toxicity of chemical treatments against the FD vector, the marginal social cost of the FD treatment considered by the planner is greater than the private cost paid by winegrowers. Let $\omega > 0$ represents the marginal environmental cost, i.e., the value of the damage caused by one treated plot on health, biodiversity of water quality (for instance). This cost is assumed to be constant and homogeneous among vineyards. Maximizing the total expected profit for all winegrowers simultaneously implies that the contamination effects of treatment choices are fulled accounted for, according to:

$$\max_{\{t_\ell\}_N} \Big\{\mathbb{E}[\Pi] \equiv \sum\nolimits_{\ell \in N} \left[(1 - p_\ell) r_\ell - (c + \omega) t_\ell\right]\Big\}. \tag{8}$$

The *bang-bang* structure of the solution obtained previously is maintained for this social program, when expected profits are maximized simultaneously taking into account the two dimensions of treatment externalities (protection effect against the diffusion of FD and environmental damage). Vineyards that should be treated under the socially optimal allocation of treatment are those for which:

$$-\frac{\partial p_\ell}{\partial t_\ell} r_\ell - \sum\nolimits_{j \neq \ell} \frac{\partial p_j}{\partial t_\ell} r_j > c + \omega \tag{9}$$

The left hand side of the equation represents the marginal gains of treatment on plot ℓ for both self-protection (first term) and the positive externalities on others vineyards $j \neq \ell$ (second term). The right hand side of the equation represents the marginal social cost of the treatment, i.e., the sum of the private marginal cost of pesticide application and their environmental marginal cost. We see that the two externalities that distinguish the first order conditions for social optimum from private equilibrium work in opposite directions. The additional environmental cost of FD treatments would require to have less vineyard plots treated whereas the positive spillover effects would require more plots to be treated relatively to the private decisions.

Considering reasonably that the public regulator is farseeing (i.e., makes sophisticated anticipations), we replace the partial derivative of the probabilities of contamination w.r.t own treatment ℓ by Equation 5 and the derivative w.r.t other treatment $j \neq \ell$ by Equation 4. Thanks to the linear probability model from uniform distribution of the random term, $\frac{\partial p_j}{\partial t_\ell} = \frac{\partial y_j^*}{\partial t_\ell}$. In addition, for $j \in N_\ell$, the direct effect of the treatment of ℓ on the probability of contamination of j is taken into account by the indicator function $\mathbb{I}$ (this effect of treatment is equal to zero for vineyard plots that are not in the first-order neighborhood of ℓ). Then, the socially optimal treatment decision rule for any given vineyard plot ℓ on the whole N vineyards depends on the following condition:

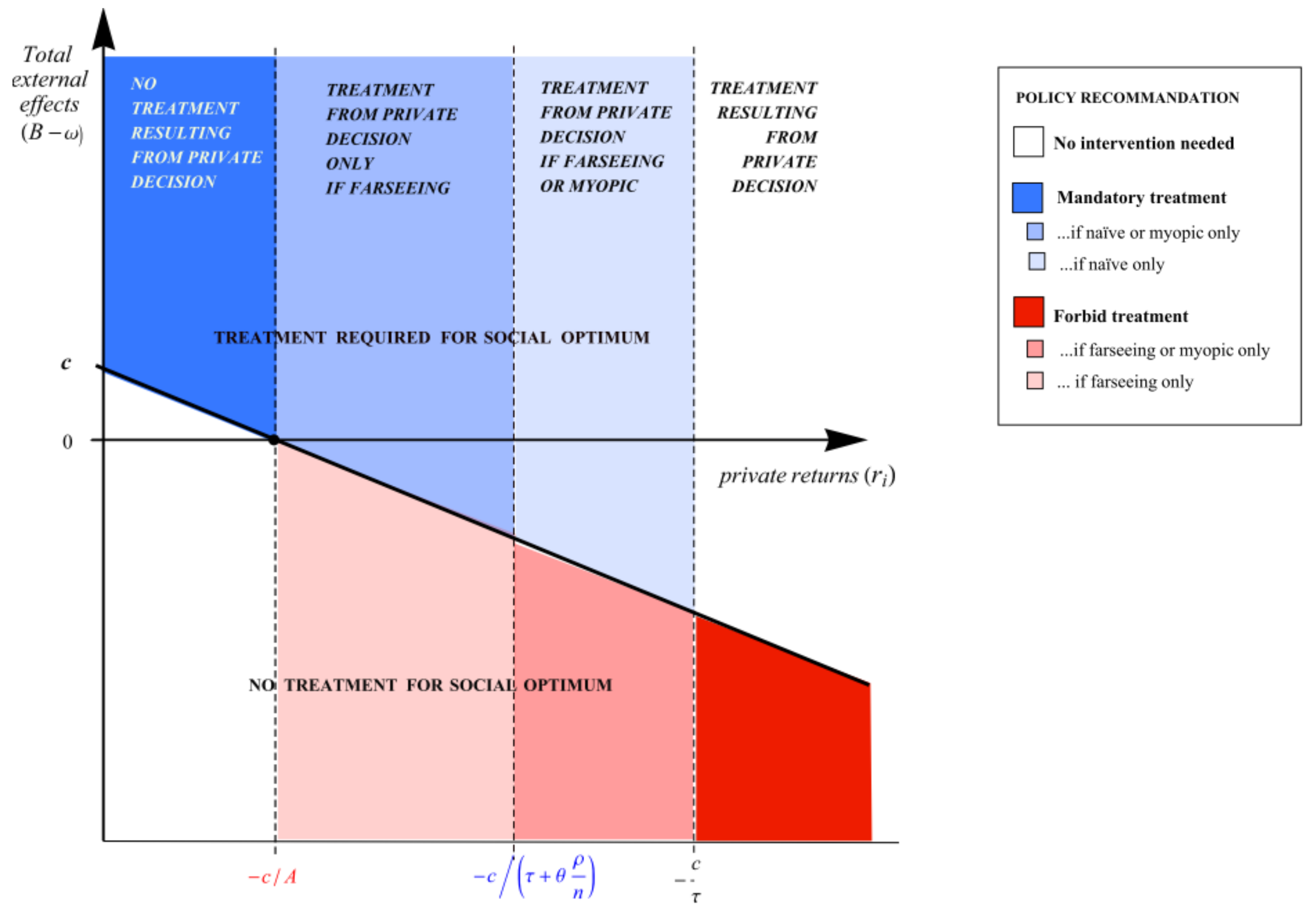
$$\underbrace{-\left[\tau + (\rho/n)\theta + (\rho/n)^2 \sum_{j\in N_\ell} \Psi_j\right]}_{A>0} r_\ell - c > \omega - \underbrace{\left[-\sum_{j\neq\ell}\left[(\theta/n)\mathbb{I}\{j\in N_\ell\} + (\rho/n)\Psi_j\right] r_j\right]}_{B>0} \tag{10}$$

The left hand side accounts for the net private marginal returns from treatment for plot ℓ, as anticipated by a farseeing regulator. The right hand side accounts for the total marginal external costs of treating plot ℓ, the negative effect on the environment (ω) and the positive effects on other winegrowers (B). The trade-off of Equation 10 is illustrated in Figure 2 where the x-axis represents private returns r_ℓ and the y-axis, the difference $B - \omega$ between the positive externality (protection) and the negative externality (pollution). Equation 10 is represented by the bold line $B - \omega = c - A \cdot r_\ell$. For any given vineyard private returns, the plot should be treated at the social optimum if the total external effects are above the line, and not treated if the total external effect is below. For the sake of comparisons, the private decision rule of individual producers are reported from Figure 1 (thresholds are vertical lines depending upon types of anticipation). As winegrowers do not account for externalities in their private choices (B and ω), even farseeing producers' choices may diverge from optimal ones. There is a coincidence between private and social optimal treatment decision (the white areas on Figure 2) only when either private returns are low and environmental damages very high, or when both private returns and positive protection externalities are very high. In general, policy recommendations will vary along with individual characteristics of winegrowers (revenues and type of anticipations).

Note that the decentralization of the social optimum on each plot with classical market instruments such as taxes is difficult for several reasons. First, as expected with two externalities, two instruments are required: a tax for the environmental damage, and a subsidy for the protection effect. While the environmental tax could be uniform across producers under our assumption of equal marginal damage across space, the marginal benefit from protection depends on local characteristics such as the private returns from the neighbors and subsidies should be targeted. The fact that both externalities stem from the same source make politically difficult to implement a

Figure 2: **Private decisions, social optimum, and policy recommandation for treatment**

Notes: The Figure compares the private decisions about treatment applications with the social optimum, and describes the policy implications to align them. Private decisions coincide with to social optima in white areas, without treatment application on the left (for small private returns and relative high pollution) and with treatment application on the right (for high privates returns and relative high protection spillovers). Inbetween, the correspondence depends on the assumed anticipations. Mandatory treatments are more relevant for naive anticipations, small private returns, and high protection externalities; forbidden treatments are more relevant for farseeing anticipations, high private returns, and high pollution externalities.



policy that would tax pesticides for some producers while subsidizing them for others (especially if subsidies are targeted for the most profitable vineyards). Moreover, aligning private incentives for treatment and social optimum raises informational issues, as myopic or naive producers do not maximize their true expected profit, and the regulator is unlikely to be fully aware of the type of anticipations of every producer. This calls for another combination of instruments. Paradoxically, command-and-command instruments such as locally-determined mandatory treatments or local treatment prohibitions may be easier to implement, as the knowledge of winegrowers' anticipations is not required. From Figure 2, the variations in the blue and red areas show that depending on anticipations, mandatory treatments or prohibitions may be unnecessary as producers would have made the right decision on their own initiative. Nevertheless, such policies make possible to achieve the social optimum throughout the territory, subject to knowledge of certain parameters that we will now estimate.

4 Empirical Application

4.1 Matrix notations

The probability of contamination from Equation 1 is a spatial econometric specification with binary outcome (Pinkse and Slade, 1998; LeSage and Pace, 2009). More precisely, it corresponds to a Spatial Durbin Model where both the spatially lagged outcome variable and a lagged explanatory variable are present in the right hand side of the equation. Matrix notations that are more appropriated to compute the marginal effects of treatment choices and to present the estimation method. In effect, the direct effect of treatment from the spatial econometric literature Abreu et al. (2004); LeSage and Pace (2009) corresponds to the private effect for farseeing anticipations and the total effect is the social effect of treatments, independantly from which receive the benefits.

Consider the two $N \times N$ spatial weight matrix M and W with the generic terms respectively m_{ij} and w_{ij}. We set $m_{ii} = w_{ii} = 0$ by convention, this is equivalent to consider that the choices of plot i does not have a direct spillover effect on itself (i.e., no direct reflexive effect). In addition, the spatial econometric literature typically row-standardize to have rows that sum to unity. This generalizes the local average presented in the theoretical model where $w_{ij} = m_{ij} = 1/n$ with:

$$\tilde{\boldsymbol{t}} = M\boldsymbol{t} \quad \text{and} \quad \tilde{\boldsymbol{y}}^* = W\boldsymbol{y}^* \tag{11}$$

Matrix notations allow to write a *reduced form* where the outcome probability is factorized to make the derivation of the effect of treatment applications easier. Accordingly, the contamination level measured by the latent variable for each vineyard plot writes, by noting I the $N \times N$ identity matrix:

$$\boldsymbol{y}^* = \rho W\boldsymbol{y}^* + B(X; \boldsymbol{\beta}) + \tau\boldsymbol{t} + \theta M\boldsymbol{t} \tag{12}$$

$$= (I - \rho W)^{-1} \left[B(X; \boldsymbol{\beta}) + (\tau I + \theta M)\,\boldsymbol{t}\right] \tag{13}$$

The complex spatial interactions from the interdependence of contamination (spatially auto-regressive) and treatment effects between neighbors are represented by the inverse of $(I - \rho W)$ which is the sum of an infinite series that converge under the restriction $\mid \rho \mid < 1$ that we assume. In particular, we use the notations of LeSage and Pace (2009) to detail the infinite series expression for the inverse:

$$S(\rho) \equiv (I - \rho W)^{-1} = I + \rho W + (\rho W)^2 + \cdots \tag{14}$$

Assuming a Gaussian distribution for the errors allows to specify a spatial probit model. Accordingly, we note ϕ the probability distribution function of a standardized Gaussian distribution and we rewrite the derivative in matrix form by noting $D\{\phi\}$ the $N \times N$ diagonal matrix with

$\phi_i \equiv \phi[y_i^*]$ as the generic term:

$$\frac{\partial \boldsymbol{p}}{\partial \boldsymbol{t}^\top} = D\{\phi\}S(\rho)[\tau I + \theta M] \tag{15}$$

$$= [D\{\phi\} + \rho D\{\phi\}W + \rho^2 D\{\phi\}W^2 + \cdots] \times (\tau I + \theta M) \tag{16}$$

All the marginal effects of treatment applications on the probability of FD contamination can be recovered from this single $N \times N$ matrix of derivative, as the direct and indirect effects presented in details by LeSage et al. (2011). The direct effects are on the diagonal of the matrix, they represent the effects of the treatment of i on its own probability of being contaminated. This effect takes into account all the spatial interactions transmitted by the other winegrowers, and corresponds to the derivative of the effect of the treatment for the farseeing anticipations in the theoretical model. The indirect effect of the treatment of i is the sum of the *ith* column (without the diagonal term) that represents the marginal effect of the treatment of i on the probability of being contaminated of all other winegrowers. The sum of direct and indirect effects is the total effect, which corresponds to the marginal effect of the treatment for the social planner, where the effects on the treatment of i on other winegrowers is taken into account. The indirect effects correspond to the spatial spillovers due to the protection effect that the own treatment supply to other winegrowers.

4.2 Estimation

The spatial econometric literature has long recognized the computational problems of estimating binary outcome models with spatial interaction through usual methods such as full maximum likelihood (Anselin, 1988). In effect, this supposes the computation of N integrals or the inversion of $N \times N$ matrix at each iteration, which is burdensome for $N \approx 10,000$. Alternative estimation methods have been developed, among which we focus on 3 different methods: Bayesian Markov Chain Monte Carlo (MCMC, LeSage, 2000; Wilhelm and de Matos, 2013), Approximate Maximum Likelihood (AML, Martinetti and Geniaux, 2017) and linearized Generalized Method of Moments (GMM, Klier and McMillen, 2008). These methods of estimation have the interest of being easily available as R packages, respectively spatialprobit, ProbitSpatial and McSpatial. The bayesian MCMC method is the most used method in the literature; and is used as the reference method here. The AML method is used as a robustness check, in order to provide a estimation of the uncertainty associated to the estimation method. The GMM method is generally considered as more robust than other to departures from restrictive assumptions about errors (Gaussian distribution, homoscedasticity). Moreover, the prospect of efficiency generally attributed to ML or MCMC becomes questionable when the spatial interactions are specified *ex ante* through the spatial weight matrix as an approximation. Nevertheless, the full GMM estimation procedure implemented in the `ProbitSpatial` and `McSpatial` packages is very long to converge, we prefer instead the linearized version of the latter package. However, the linearization required by this method was shown to be quite imprecise where the degree of spatial autocorrelation is high (Klier and McMillen, 2008), which is the case here. Consequently, we do not report the results from this third method of estimation, they are available from authors upon request. The two methods of estimation are tested for different spatial weight matrix W and M to also assess the dependence of the results to the specification of spatial relationships.

4.3 Cost-benefit analysis

In order to simulate private decisions and compare different policy options in terms of cost/benefit ratio, private returns from wine production are derived from vineyards prices available for 2016 at the national scale: http://agreste.agriculture.gouv.fr/donnees-de-synthese/prix-des-terres/. These data are transformed in annual private returns using the capitalization formula, as it is standard for perennial crops (Alston et al., 2013):

$$v_i = \sum_{s=1}^{+\infty} \frac{(1+\gamma)^s}{(1+\delta)^s} r_i = \frac{r_i}{\delta - \gamma} \tag{17}$$

where δ is the discount rate and γ the growth rate.

Because the FD contamination is incurable and the winegrower has to uproot the contaminated plants in the current policy scheme, we consider contamination as a loss of capital stock that can be recovered after three years. In general, winegrowers have their first harvest approximately two years after planting (for the second leaf), we add one year to take into account the loss of yields and loss of quality inherent to new plants compared to older. We estimate the cost of a FD contamination as the discounted loss of three years of annual revenue, that is to say $R_i = \frac{\delta^2+\delta\gamma+\gamma^2}{\delta^2} \times r_i = \frac{\delta^2+\delta\gamma+\gamma^2}{\delta^2} \times v_i \times (\delta-\gamma)$. In the simulations performed below, we retain $\delta = 0.05$ and $\gamma = 0.03$, then $R_i = 1.96 \times r_i \approx 0.04 \times v_i$, approximately 4% of the whole value of the vineyard contaminated.[3] Multiplying this loss by the probability of contamination allows to obtain the expected economic cost of contamination. The benefit of the treatment, i.e., the expected value of avoided losses with treatment, is obtained by multiplying the probability difference with and without treatment to the discounted loss.

From matrix notations, we can compute the private and social expected marginal benefits from treatment, which the former depend on the anticipation by the winegrowers about the impact of their own treatments. These marginal benefits equal the derivative of the probability of contamination times the expected loss that follows the contamination and are given by:

$$\boldsymbol{v}_N = -D\{\phi\}\tau\boldsymbol{R} \tag{18}$$

$$\boldsymbol{v}_M = -\operatorname{diag}\big[(I+\rho W)D\{\phi\}(\tau I+\theta M)\big] \circ \boldsymbol{R} \tag{19}$$

$$\boldsymbol{v}_F = -\operatorname{diag}\big[S(\rho)D\{\phi\}(\tau I+\theta M)\big] \circ \boldsymbol{R} \tag{20}$$

$$\boldsymbol{v}_S = -\Big\{\boldsymbol{R}^\top\big[S(\rho)D\{\phi\}(\tau I+\theta M)\big]\Big\}^\top \tag{21}$$

where the subscripts N, M, F, and S stand respectively for naive, myope, farseeing winegrowers, and the social planner. In what follows, these expected marginal benefits will be compared with the private marginal cost of FD treatments, that will be set to 25€/ ha, an evaluation consistent with the upper evaluation in expert opinion (J. Grossman, personal communication). Taking the upper evaluation is justified to take into account some non-monetary cost associated with treatment

[3] These values for δ and γ correspond to what is usually found in the literature (e.g., Ay and Latruffe, 2016). Our empirical results are globally robust to this choice.

applications. The tax below are also simulated on a per ha basis, proportional to the vineyard area treated again the FD vector.

5 Data

5.1 Outcome variable

The empirical application is implemented at the *commune* scale (french municipalities, $N = 36,523$ for the whole country) from an original data set on FD contamination and treatments that has never used for economic evaluation before.[4] Among all the *communes*, 6772 (18.5%) have some vineyards in 2016 according to the official statistics.[5] We obtain additional data from the French Ministry in charge of Agriculture about the *communes* that have experienced a FD contamination between 2013 and 2016, and the *communes* under Mandatory Control Perimeter (MCP) in 2013. The left panel (a) of Figure 3 presents the spatial distribution of these two main outcome variables for the empirical analysis. We consider a *commune* as contaminated if at least one contaminated vine plant was found on its territory on the 2013-2016 period. To limit the simultaneity between contamination and treatment applications, we use the MCP status of 2013 for each *commune*. Accordingly, observed treatment are based on previous contamination instead of contamination that have taken place after 2013, potentially because of FD dispersion. This is important to study the causal effect of treatment on contamination rather than the converse. In the absence of data about effective treatments, we assume that winegrowers fully comply with the actual MCP policy. The right panel of Figure 3 displays the distribution of annual returns computed from 2016 vineyard prices according to the capitalization formula. Under the assumption that $\delta - \gamma = 0.02$, the per-ha returns from wine production are distributed between €363 and €24,874 with an average of €1,655.

[4] We use data at an administrative level while the theoretical model is developed at the producer's level. Trying to infer individual behavior from group-level data relates to the problem of ecological inference (King et al., 2004) that we do not consider here.

[5] The official statistics report only vineyards claimed to harvest grapes. Abandoned vineyards, presented as an important determinant of disease dispersion by Pavan et al. (2012), are not reported in a national database and can not be used in this study.

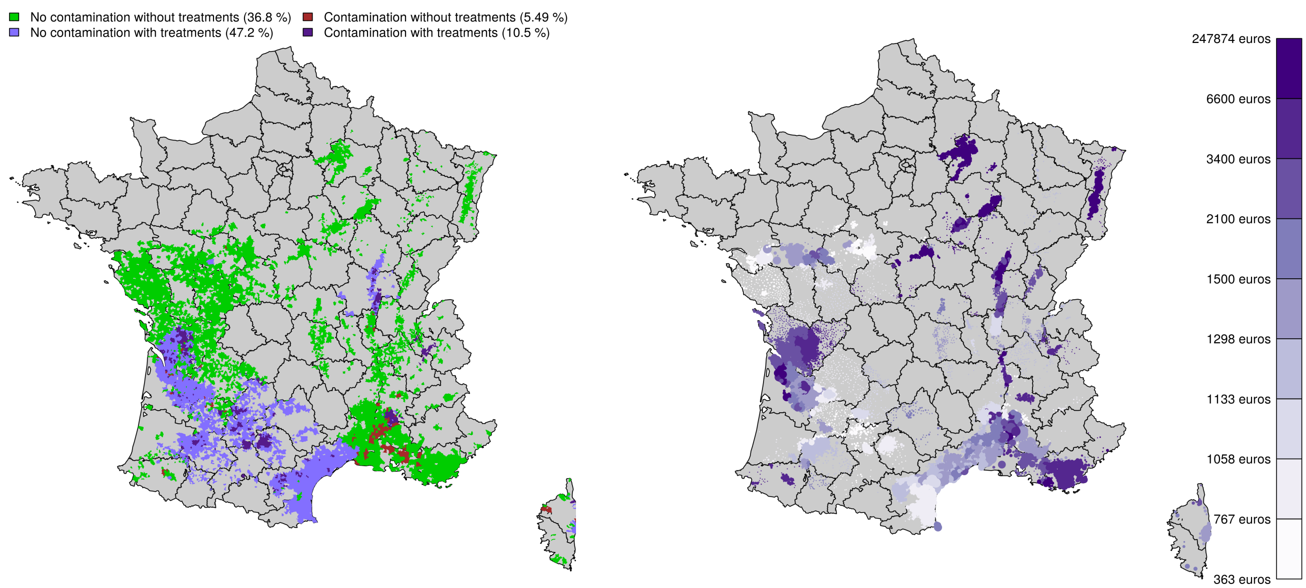
The spatial distribution of these returns from wine production are closely related to the presence of geographical indications with high values for the *Champagne* region (the northernmost region) and for the *Bordeaux* region (South West region).

Figure 3: **Spatial distribution of vineyard, contamination, treatment, and per-ha returns**

Notes: For the *communes* with a positive vineyard area (N = 6772), the left panel (a) reports their MCP status in 2013 crossed with FD contamination patterns (2013-2016). The right panel (b) reports the annual returns computed from the capitalization formula with point size proportional to acreages; the scale presents the deciles of the distribution.

(a) MCP status crossed with FD contamination

(b) Annual returns weighted by acreages



5.2 Exogenous variables

We use the *commune* scale to merge additional data about bio-climatic variables, as presented in the Table 5 in the Appendix. The climate data come from an spatial interpolation from the average 1970-2010 interpolated by *Météo France*. They contain average values for annual temperature, cumulative precipitations, solar radiation, wind speed, and relative humidity. The average elevation of each *commune* is added to the data set. These variables are used to estimate the ecological niche of the FD vector, as it is typically the case in species distribution models and presented in the theoretical part of the paper. Used as predictors, these variables allow to improve the goodness-of-fit of the model of FD contamination. This is of particular importance to simulate the spatial patterns of FD dispersion and the effects of treatment application on the probability of being infected.

5.3 Spatial weight matrix

In the absence of strong theoretical *a priori* about the spatial dependence between *communes* in the dispersion of the FD disease and the protection effects of treatments, the common practice in spatial econometrics is to consider a panel of spatial weight matrix and to evaluate the robustness of the results relative to the shape of the matrix. We select four contrasted types of spatial weight matrix (contiguity, Delaunay triangulation, closest neighbors, and distance threshold) crossed with different parameter to sweep the spectrum of potential spatial dependencies. The resulting eight spatial weight matrix are presented in the following Table 1. The matrix that is most in accordance with the theoretical model is the contiguity matrix at order 1 (reported at the first row). Using this matrix to compute the spatial dependence of contamination levels or insecticide treatment amounts to compute $\tilde{y}_i^*$ and $\tilde{t}_i$ as the average for the *communes* with at least one border in common with the *commune* i. With this matrix approximately 0.06% ($29202/6672^2$) of all possible links between *communes* are different from zero. Considering five-order contiguity as in the second row of the Table, allows these numbers to increase to approximately 0.8% ($393344/6672^2$) of possible links that are different from zero. In addition to these two contiguity matrix that depend on the geographical shapes of *commune* polygons, we use triangulation methods that neglect the geometry of *communes* by focusing on centroids. The difference between sphere of influence and relative neighborhood is based on the algorithm that select the neighbors among all possibles (see Bivand et al., 2008). Closest neighbors matrix allow to have a constant number of neighbors for each *communes*, and threshold matrix allow to consider spatial interactions as the crown flies, putting more importance on physical distances. All these binary spatial matrix (*communes* are neighbors or not) are chosen to be most contrasted as possible, we also test the same eight matrix with a inverse squared distance weighting scheme, in order to take into account the relative remoteness of each *commune* in a given neighborhood. The results are robust to this point, we report here only the results from binary (while row-standardized) spatial weight matrix.

Table 1: **Descriptive statistics about the spatial weight matrix**

Type	Param	Sym	N	$\neq 0$	Mean	Min	Q1	Q2	Q3	Max
Contiguity	1	TRUE	6772	29202	4.31	0	3	4	6	16
Contiguity	5	TRUE	6772	393344	58.08	0	29	54	87	160
Triangulation	Soi	TRUE	6772	31188	4.61	1	4	5	6	10
Triangulation	Rel	FALSE	6772	9050	1.34	0	0	1	2	5
Closest N.	5	FALSE	6772	33860	5	5	5	5	5	5
Closest N.	20	FALSE	6772	135440	20	20	20	20	20	20
Threshold	5	TRUE	6772	24360	3.6	0	1	3	5	16
Threshold	10	TRUE	6772	97918	14.46	0	8	13	20	48

Notes: All the matrix reported are row-normalized binary matrix. The Param columns reports the parameter of each specifications. For contiguity matrix, it is the order of neighborhood. For triangulation matrix, it is Soi for sphere of influence and Rel for relative neighborhood. For closest neighbors it is the number of neighbors and for threshold matrix, the distance is in kilometers. The matrix are computed with the `spdep` package. The column Sym reports the symetry of the matrix, the columns $\neq 0$ is the number of non-zero links. The last columns (from Mean to Max) are about the distribution of the number of neighbors for each observation.

6 Results

6.1 Effects of variables

The following Table 2 presents the estimations of the main parameters related to the effects of treatment applications on the probabilities of being infected, according to different spatial weight matrix and method of estimation. As discussed before, we report only the results from MCMC and AML methods of estimation because the coefficients from linearized GMM are significantly different. The latter are probably biased because auto-correlation coefficient ρ is generally higher than 0.7, which is consistent with the results of Klier and McMillen (2008). For each estimation method, we use the four classes of spatial weight matrix with different parameters. We report only a subset of eight models among the 16 possible, that are chosen to summarize the general variability of the results according to estimation method and spatial weight matrix specification.

The sign and the significance of treatment and contamination coefficients are quite stable between specifications. As expected, the presence of mandatory treatment significantly decreases the probability of being contaminated, and the spatial autocorrelation parameter about the spatially lagged effect of contamination is positive and around 0.7. This means that a high contamination level of the neighbors increases significantly the probability of being contaminated. The average treatment of the neighbors (Lag treat., the third row of Table 2) does not have a significant effect on the probability of contamination, and the sign of the estimated coefficient change between specifications. This means that the protection effects spread more effectively in space through the auto-correlation of the contamination than from treatment spillovers. In effect, treatments have a strong indirect spatial effect as they decrease the contamination level of the neighbors, which in turn decreases the own probability of contamination.

Table 2: **Econometric results from spatial probit models of contamination**

Variable [coef]	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Treatment [τ]	-0.26**	-0.67**	-0.58**	-0.73**	-0.44**	-0.66**	-0.19*	-0.09
	(0.11)	(.13)	(0.15)	(0.14)	(0.14)	(0.13)	(0.09)	(0.10)
Lag Treat. [θ]	-0.19	0.17	0.25	0.28	0.24	0.31*	-0.17*	-0.39**
	(0.12)	(.15)	(0.17)	(0.16)	(0.15)	(0.14)	(0.09)	(0.12)
Lag Contam. [ρ]	0.66**	0.71**	0.71**	0.76**	0.81**	0.81**	0.73**	0.77**
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Direct Effect	-0.02	-0.05	-0.04	-0.05	-0.03	-0.07	-0.02	-0.02
Indirect Effect	-0.06	-0.07	-0.03	-0.07	-0.04	-0.1	-0.08	-0.14
Total Effect	-0.08	-0.12	-0.07	-0.12	-0.08	-0.17	-0.1	-0.17
Estimation Mthd	MCMC	AML	MCMC	AML	MCMC	AML	MCMC	AML
Spatial Matrix	Co-01	Co-01	Tr-So	Tr-So	Cl-05	Cl-20	Th-05	Th-10
% of Good Pred.	77.8	78.5	82.2	80.7	78.3	74.5	76.4	75.5

Notes: We report raw estimated coefficients with standard error in brackets, * counts for 5% significance and ** for 1% significance. Biophysical variables are also included in the models as control variables, their effects are reported in Figure 7 of the Appendix. Marginal effects of treatment are reported as average direct effect, average indirect effect, and average total effect in the second part of the Table, according to the formula given by LeSage and Pace (2009). The method of estimation and the spatial weight matrix vary between columns. MCMC method corresponds to a Markov Chain Monte Carlo estimation, performed with the `R` package `spatialprobit` and AML corresponds to an approximate maximum likelihood estimation, performed with the `R` package `ProbitSpatial`. The details of spatial weight matrix are reported in Table 1, percent of good prediction reported in the last row are computed from predicted pobabilities with a threshold equals to the sample frequency.

The average direct and indirect effects have both the expected sign, they show that increasing directly and indirectly the treatment decrease the probability of being infected. They also show a high degree of spatial autocorrelation in FD dispersion, as the indirect effects are substantially higher than direct effects. This means that a high part the effect of treatment against the FD vector is not related to the own probability of contamination for the winegrower that applies the treatment, but through the probability of contamination of the other winegrowers in the neighborhood. The protection effect that we describe as a positive externality in the theoretical part of this article appears empirically as a strong determinant of the efficiency of treatment against FD vector. The effects of the bio-climatic variables are reported in Figure 7 of the Appendix, with a computation method described in Ay et al. (2018). The bio-climatic data show a negative effect of temperature, precipitation, solar radiation, relative humidity, and elevation on the probability of FD contamination. The non-linear effect of wind is more marked, with a negative effect on low speed that becomes positive for high speed (greater that 4m/s). Finally, bio-climatic variables, treatment choices from MCP and spatial auto-correlation of contamination levels allow to predict correctly more than 75% of 2013-2016 FD contamination on the whole France. The spatial matrix based on triangulation with sphere of influence perform best for the two methods of estimation (MCMC and AML). Consequently, we will favor the results from this specification estimated by MCMC.

6.2 Spatial predictions

Figure 8 in the Appendix shows the predicted probabilities of FD contamination according to different scenarios about vector treatment: current mandatory MCP treatments, without any treatment on the whole territory, and with treatment for all vineyard plots. Under current MCP, the spatial distribution of predicted probabilities is close to what is observed, with generally small probabilities of being contaminated: less than 10% for 90% of the *communes*. The counterfactual distributions from the other panels of Figure 8, with extreme all-or-nothing scenarios about treatment, show a relative efficiency of the treatment against the vector that could decrease substantially the probability of contamination (as it appears in the bottom-right panel of the Figure). The spatial distribution of the efficiency of the treatment is closely related to the distribution of the probability of contamination in the absence of any treatments (i.e., the panel 2 and 4 of the Figure). Intuitively, the treatment is more efficient for *communes* with high contamination levels.

Figure 4 presents the expected cost of contamination obtained from the predicted probabilities multiplied by the cost of contamination (the discounted value of 3-years loss of annual returns). The distribution of expected cost in the top-left panel (with treatment application following the current MCP regulation) shows that the spatial variations of annual returns are the main driver of cost heterogeneity. The expected cost is substantially higher in *communes* of high wine value (*Bordeaux*, *Champagne*, *Bourgogne*). By comparing the top-right and bottom-left panels, the impact of treatment on expected cost of the FD is high. Note also that the spatial patterns change significantly from the top-left panel, which indicates the importance of spatial dynamics of contamination in addition to the cost distribution to evaluate the economic consequences of FD dispersion. The spatial patterns of the difference in probability times the cost (bottom-right panel) is very close to the spatial pattern of the probabilities in the absence of treatment (top-right panel). Areas that are not currently contaminated by the disease at the North-East of the country show the highest cost of the absence of treatment but also the highest expected benefits from the treatment.

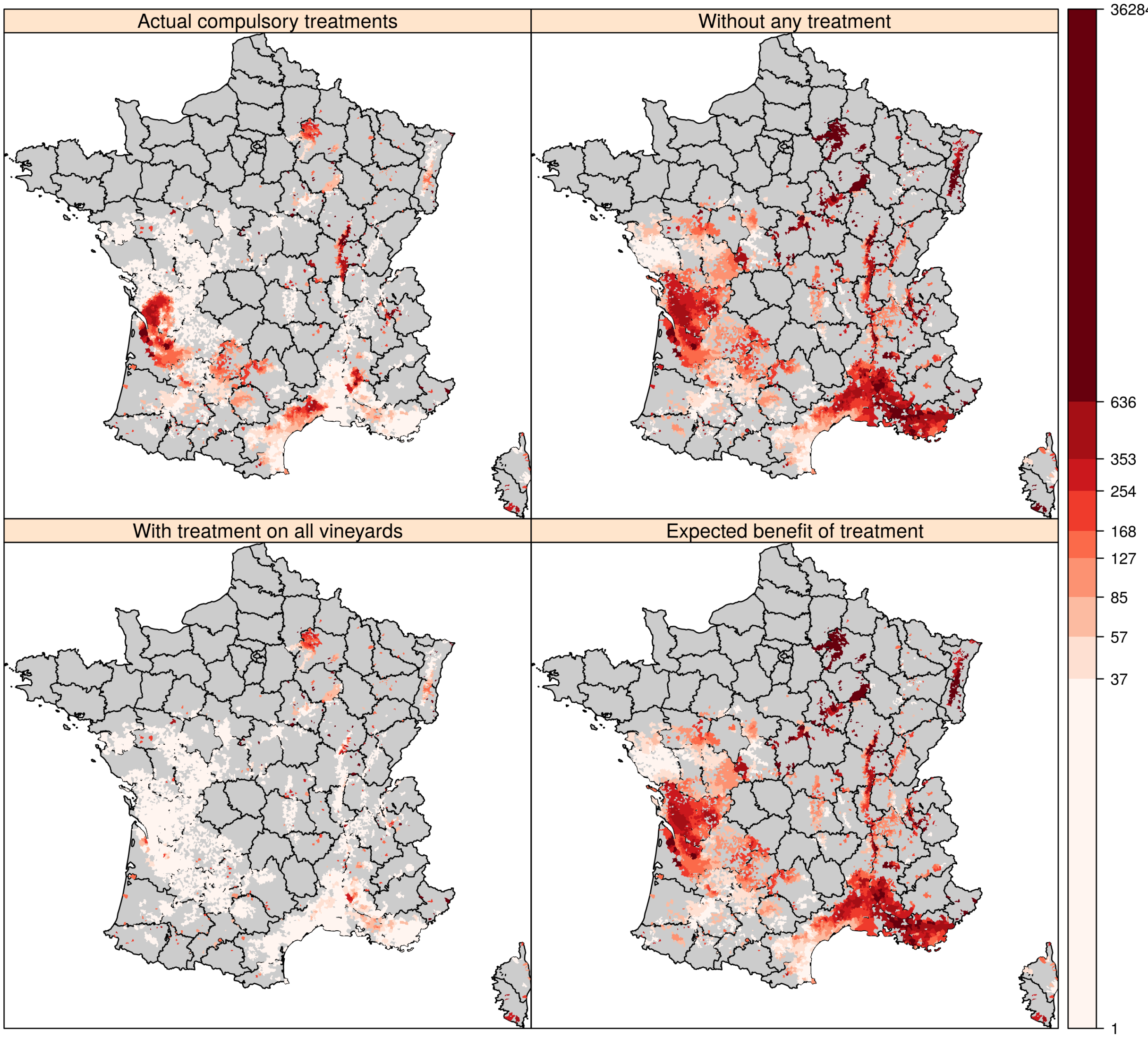
7 Simulations

7.1 Private equilibrium

We combine here the empirical results from the spatial probit model (III) to the theoretical micro-economic model in order to derive counter-factual simulations scenarios and study differentiated public policies. We consider a first counter-factual situation of the absence of any MCP policy. Accordingly, winegrowers behave following the first-order condition for profit maximization as presented in section 2.2, with differences depending on the assumption made w.r.t their anticipations. Table 3 presents the marginal benefits of treatment resulting from equations (18) to (21). The

Figure 4: **Expected cost of FD contamination for different treatment scenarios**

Notes: We multiply predicted probabilites by the cost associated to a contamination, defined as the discounted value of 3-year loss of annual returns (log scale, deciles are reported on the right). The predicted probabilities differ between panels, top-left panel reports the predicted probabilities according to current MCP, top-right panel reports the probabilities without any treatment, bottom-left panel reports the probabilities with mandatory treatment at the national scale, and bottom-right panel the difference between the second and the third multiplied by the cost. It corresponds to the expected avoided loss resulting from the treatment, this last panel is the expected benefit from treatment.



anticipated marginal benefits of treatment are trivially increasing with the level of sophistication as the spatial spillovers taken into account are higher. Consequently, both the sum of the marginal benefits and the proportion of winegrower that decide to treat are increasing with the sophistication of anticipations. The social benefit of treatment against FD is estimated at approximately €637 millions, which correspond to 2.4% of the revenue from wine production in France (equal to €26.5 billions in 2016 according to official statistics). In the case of naive winegrowers, the privately expected benefits of the treatment represent only 7.2% (45.7/637) of the social benefit (without accounting for the negative effect of pollution on the social welfare). This share increases to 23.4% (149/637) for myopic winegrowers and reaches 50.3% (320/637) for farseeing winegrowers.

Table 3: **Distribution of private and social benefits, with different anticipations**

Type	N	Mean	Min	Q1	Q2	Q3	Max	Sum	% treat
Naive	6772	67.8	0.00	6.50	22.2	56.7	11045	45.78	45.1
Myope	6772	220.1	0.00	23.76	79.1	194.7	24259	148.82	74.3
Farseer	6772	473.1	0.00	54.74	177.8	430.8	37612	320.06	86.3
Social	6772	1187.1	0.00	136.09	430.6	1065.6	88530	637.21	94.1

Notes: According to the different assumptions about private anticipations and social outcomes (in row), the Table displays for each 6,772 *communes* the mean and the quartile of the per-ha marginal benefit of the treatment. The column Sum report the sum of marginal benefits weighted by the acreages expressed in millions € . The last column represent the percent of *commune* that treat with a private cost of the treatment of € 25 but without negative externality due to environmental pollution.

The last column of Table 3 reports the share of total vineyard area that would be treated without MCP under alternative anticipations, it is obtained by comparing expected marginal benefit per ha with the private marginal cost of the treatment set at €25 per ha. The values are increasing with the sophistication of anticipations, and results on aggregated expected benefits show a significant economic value of treatment application. Even with naive anticipation, more than 45% of the vineyards are treated without any public intervention, and the share goes to 95% in the social optimum (again, environmental costs are not taken into account in these numbers).

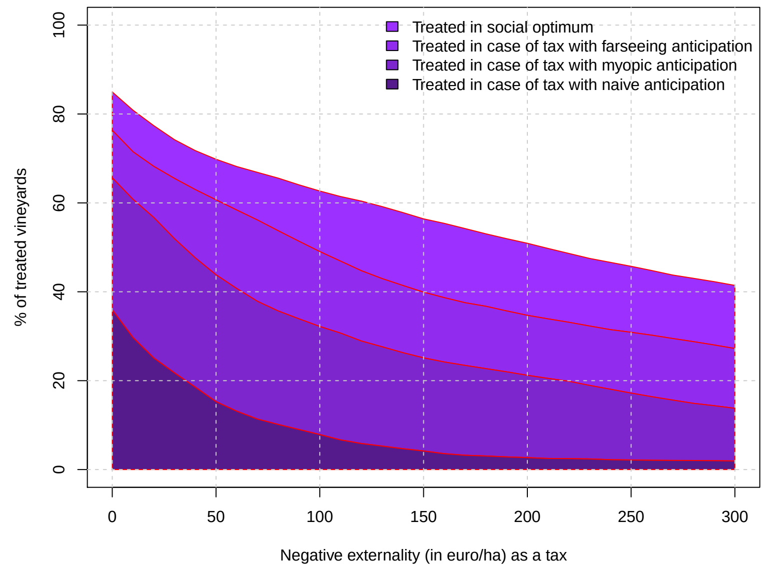
7.2 Tax on pesticide application

We now perform a simulation with a flat tax set to the level of the marginal cost of treatment in terms of environmental pollution. Because no reliable estimate can be found in the literature for the value of this environmental cost, we perform simulations letting the social per-ha cost (and the identical per-ha tax) vary between 0 and €300. The consequences in terms of treatment choices are displayed in Figure 5. When the marginal environmental damage increases, the share of vineyard that should optimally be treated decreases from 95% of the total area without pollution costs, to about 40% with a damage set to €300 per ha. Our results also indicate that a Pigouvian tax aimed at internalizing the negative externalities of pesticide use does not allow to recover the social optimum from private choices: as can be seen on the figure, winegrowers systematically under-provide treatment (the shares of treated areas based on private choices with a tax lie below the social optima). This is true even for high values of the pollution externality, and for any assumption about winegrowers' anticipations. This results is explained by the positive protection effects of treatment that are not taken into account by producers. Naturally, more sophisticated anticipations lead to more efficient treatment areas (i.e., closer to the social optimum) as farseeing winegrowers' anticipations account partially for this protection effect.

Note that the picture from previous Figure 5 is incomplete as it compares only aggregate acreages. The next Figure 6 shows that the under-provision of treatment obtained is in reality a spatial mismatch between areas that should be treated and those that should not according to the social optima. As in Ambec and Desquilbet (2012), producers' anticipation matter for policy recommendations, and we observe that for high value of the negative externality, naive anticipations require less intervention and are closer to the social optimum, while this did not appear on the previous graph. The interpretation is straightforward. Because of the two externalities, two instruments are needed. The social optimum could be decentralized with the combination of a tax equal to the marginal environmental cost and subsidies equal to the positive protection spatial spillovers computed from the spatial probit model. Note that the type of anticipations made by

Figure 5: **Percentage of treatment according to different levels of pollution**

Notes: For each value of the negative pollution externality (x-axis) the Figure reports the social optimal percentage of treated vineyards, and the private percentage of treated vineyards according to different assumptions about the anticipation and with a treatment cost of €25 plus a flat tax equal to the amount of the pollution externality.



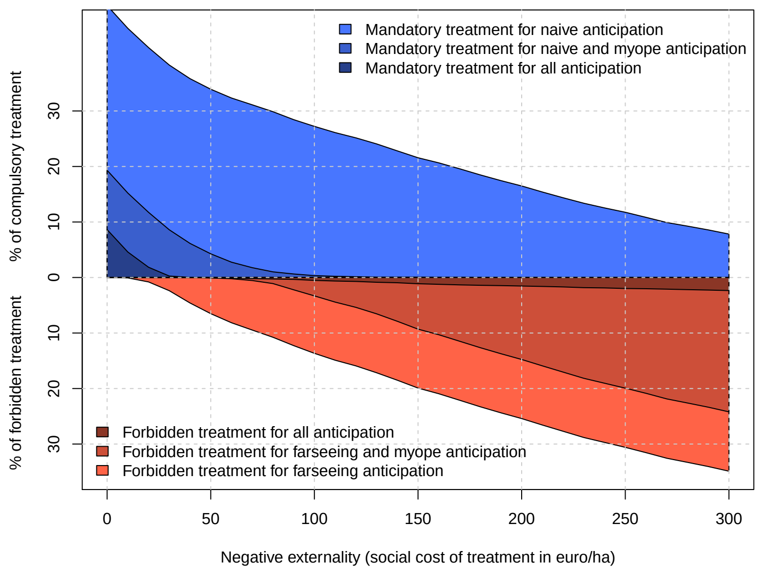
producers would matter for the optimal design of such a combination of instruments. In particular, the amount of subsidies would be differentiated according to the anticipations of winegrowers, in addition to the economic returns of those neighbors that benefit from the positive externalities. The design of such a policy would be interesting in its own, but is outside the scope of the paper.

7.3 Evaluation of current policy

Lastly, we use our simulations to evaluate the efficiency of the current MCP policy in terms of the spatial concordance (good targeting of *communes* for which it is socially optimal to treat), compared to a decentralized policy aimed at bringing together private behaviors and social outcomes, for varying values of the negative environmental externality of the treatment. Table 4 shows that the current policy of MCP is usually less efficient than a flat tax policy with a tax equal to the marginal environmental damage, even in the case of naive anticipations. Nevertheless, the performance of a tax in terms of targeting of a tax is decreasing with the value of the negative externality if producers are myopic or foreseers, while it is increasing under naive anticipations and the current policy.

Figure 6: **Predicted probabilities of FD contamination for different treatment scenarios**

Notes: For each value of the negative pollution externality (x-axis) the Figure reports the percent of vineyard acreages that have to be mandatory treated and where the treatment must be forbidden. Without any pollution externality (i.e., x= 0) the private benefits of treatment are smaller than the social benefits and treatment is under-provised everywhere. The area of compulsory treatment (in blue) is large, in particular if winegrowers' anticipations are not sophisticated. In the oppposite case of a high environmental cost, the social benefits of treatment are generally less that the private benefits, and the area of forbidden treatment (in red) is large, in particular if winegrowers' anticipations are sophisticated.



These results stem from the fact that the under-provision of treatment application in the two latter scenarios becomes socially more relevant when the negative externality is high. The advantage of the tax policy with farseeing anticipation is maintained for all the value of the negative externalities, even for an extreme value of €500/ ha. It is particularly striking to see that for naive anticipations and non-zero values of the negative externality, the compulsory MCP policy is closer to the social optimum than tax in the case of naive anticipations. In other words, the current regulatory MCP scheme proves relatively effective if winegrowers are expected to be naive.

Figure 9 in the Appendix maps the spatial mismatch under alternative scenarios regarding the environmental costs of pesticides, for the current MCP policy and for a market-based tax instrument. Grey and orange areas represent a good targeting (respectively, treatment and no treatment when it is socially optimal to do so). Yellow and pink areas represent a spatial mismatch (respectively, treatment and no treatment when the opposite would be socially optimal). First regarding the current

Table 4: **Percent of good targeting of the current MCP policy and alternative tax policies**

Tax/ externality values	0	50	100	250	500
Current policy	47.41	60.73	67.92	76.66	75.84
Tax with naive	52.01	55.06	63.00	67.04	68.83
Tax with myope	83.31	79.84	71.90	68.69	65.06
Tax with Farseer	93.46	90.87	89.70	88.09	86.19

Notes: The table reports the percent of *communes* with wineyards that are correctly targeted by each policy according to the value of pollution externalities (assumed to be equal to the flat tax used to decentralize it). Correct targeting is defined as the concordance with the social optimum, both in terms of treatment and absence of treatments.

policy, the simulations suggest that if the negative externality is not too high, mandatory treatments limited to MCP areas result in an inefficient lack of treatment in very large areas (in pink). In other words, the spatial miss-match of current policy (as measured by the difference between 100 and the % reported in Table 4) essentially consists of a treated area that is too small. Only for scenarios with very high environmental costs does the current MCP strategy yield a relatively good spatial matching of 75%, and this is largely driven by areas where no treatments are socially optimal (in orange). Under the estimated probabilities of contamination, the *Bordeaux* and *Bourgogne* areas remain in (optimally) treated areas even for high environmental costs, while for some lower-valued vineyards in the Southwest of France, mandatory treatments should be given up for high environmental costs.

When environmental costs are internalized with a tax policy and treatment decisions decentralized to individual winegrowers, the only possible spatial mismatch is an under-provision of treatments (pink areas). Winegrowers' anticipations are then crucial when evaluating the efficiency of their private decisions. Unsurprisingly, naive anticipations result in an inefficiently low share of treated areas, even when the environmental damage is high. Conversely, accounting for sophisticated feedback effects (in farseeing anticipations) results in a quite good spatial matching between private and social treatment decisions. In particular, relying on private profit maximization with sophisticated anticipations allows large areas that are insufficiently treated under current regulations (in the South-east of France or in *Champagne*) to be treated, while the environmental damage is internalized. Actual safe regions could have an interest to treat as it is found by the CLIMEX analysis performed by an EFSA panel Jeger et al. (2016), which strongly suggests that the vector is likely to be able to establish over most of the EU territory and, in particular, in all northern and central European grapevine-growing areas. Although the way winegrowers form their anticipations is beyond a public regulator's control, providing winegrowers organization with quantified estimates of probabilities of contamination and private returns to own treatment should probably be considered.

8 Conclusion

In this paper, we contribute to the economic analysis of a plant-disease diffusion by providing a spatially-explicit characterization of the probability of contamination by FD in France and by investigating the role that individual characteristics of winegrowers play, including their degree of sophistication in accounting for feedback effects of their own treatment choices. We also discuss the optimal regulations when both positive treatment externalities and negative environmental impacts are taken into account. The econometric specification allows us to evaluate the efficiency costs of the present regulations and the spatial concordance of alternative tax policies in targeting socially-optimal treatment areas. The combination of sophisticated anticipations and a flat tax equal to the marginal damage from treatment application is the second-best solution. Farseeing anticipations could be facilitated by the public regulator by disseminating quantitative estimates of risks and private returns to treatments among professional organizations. Because of spatial externalities, the first-best could only be reached with an additional, spatially-differentiated subsidy aimed at internalizing properly protection externalities : however, such a policy would be difficult to implement in practice.

Some aspects would deserve further investigation. First, FD is a quarantine disease in the European Union subject to mandatory reporting. In this paper, we have considered that mandatory regulations such as pesticide application and removal of contaminated plants were effectively implemented within MCP areas. However, because the disease does not cause an immediate death of the vine, and because of concerns regarding adverse health and environmental effects of pesticides, effective participation of winegrowers to the mandatory control of the vector population is not guaranteed. For example, in 2014, an organic producer in *Bourgogne* faced lawsuits for refusing to use Pyrevert, an insecticide that is authorized for use in organic agriculture, arguing that there was no evidence of contamination of his own plots, and that the treatment would kill beneficial insects as well. This highly publicized case could be the tip of the iceberg, and further analysis of winegrowers' decision making (where social interactions could be taken into account) could be undertaken.

Second, in this paper we neglected other potential sources of contamination, as planting of contaminated vines (resulting in the FD being introduced in a region without spatial dissemination), we built on the assumption that vines (*Vitis vinifera*) are the specific host of both the phytoplasm causing FD and its vector (it is not observed on other plant species), while recent research seems to be less affirmative. According to Jeger et al. (2016), historical evidence on 30 European outbreaks suggests that spread by vector represented only 57% of contamination, while contamination due to propagative material (infected young plants) accounted for 37% of outbreaks, and 2% from wild reservoir. Moreover, the first pillar of the strategy against the FD is vineyard surveillance, that is not modeled here in the absence of reliable data. It is nevertheless a crucial aspect of any containment strategy, to which more researches from social sciences should be dedicated.

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10 Authors Contributions

Estelle Gozlan and Jean-sauveur Ay contribute to conception and model design, acquire data, perform the analysis, draft and revise the article, and approve the final version.

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A Appendix

Table 5: **Descriptive statistics of the main variables**

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
New FD contamination [binary]	6772	0.071	0.258	0	0	0	1
Compulsory FD treatment [binary]	6772	0.380	0.485	0	0	1	1
Average vineyard price [1000 euro/ ha]	6681	82.730	253.000	4.000	11.000	39.000	3387.000
Average annual temperature [degree]	6772	12.490	1.420	2.512	11.570	13.380	16.490
Average cumultive precipitations [mm]	6772	63.060	12.180	38.250	55.840	66.980	148.200
Average solar radiations [millions J]	6772	0.834	0.029	0.708	0.812	0.859	0.915
Average wind [meter/ second]	6772	2.664	0.699	0.813	2.177	3.060	6.096
Average relative humidity [%]	6772	75.370	4.398	61.630	73.770	78.510	84.660
Average elevation [meter]	6772	196.400	170.900	1	79	269	1923

Notes: Sample is limited to viticultural *communes*, price data are not available for 91 of them. FD contamination is computed from the 2013-2016 period, compulsory treatment (MCP) corresponds to 2013. Climatic variables are 1970-2010 averages, interpolated from *in situe* observations by *Météo France*.

Figure 7: **Marginal effects of biophysical variable on the probability of contamination**

Notes: Polynomial marginal effects are computed with probability predictions from reduced formula and all other variables fixed at their sample means (see Ay et al., 2018). The predictions reported are from Model (III) of Table 1 with triangulation spatial matrix based on sphere of influence estimated by MCMC. The shapes of the effects are robust to the specification of the spatial weight matrix and the method of estimation.

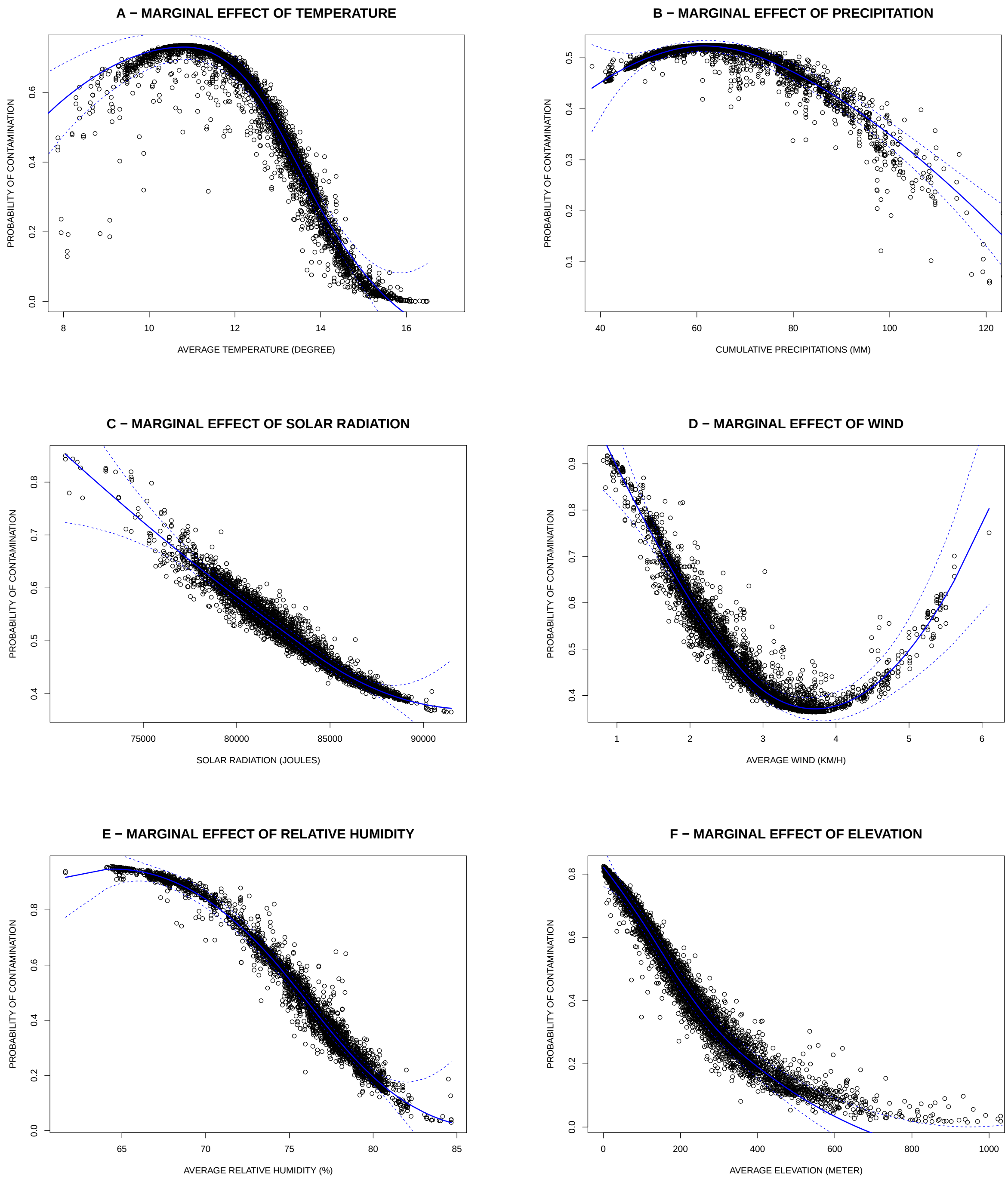


Figure 8: **Spatial distribution of predicted probabilities of FD contamination**

Notes: Predicted probabilities are from Model (III) of Table 1 with triangulation spatial matrix based on sphere of influence estimated by MCMC. The predicted probabilities are small (smaller than 10% for 90% of *communes*), so we use a log scale as it appears from the right scale of the figure. The first panel reports actual probabilities computed with mandatory treatments from current MCP scheme. The second panel reports the distribution of probabilities without any treatment on the national territory, the third panel represent the probabilities of FD contamination with all *communes* that treat, and the last panel is the difference between the second and the third, displaying the decrease in the probability due to the treatment against FD vector in the whole country.

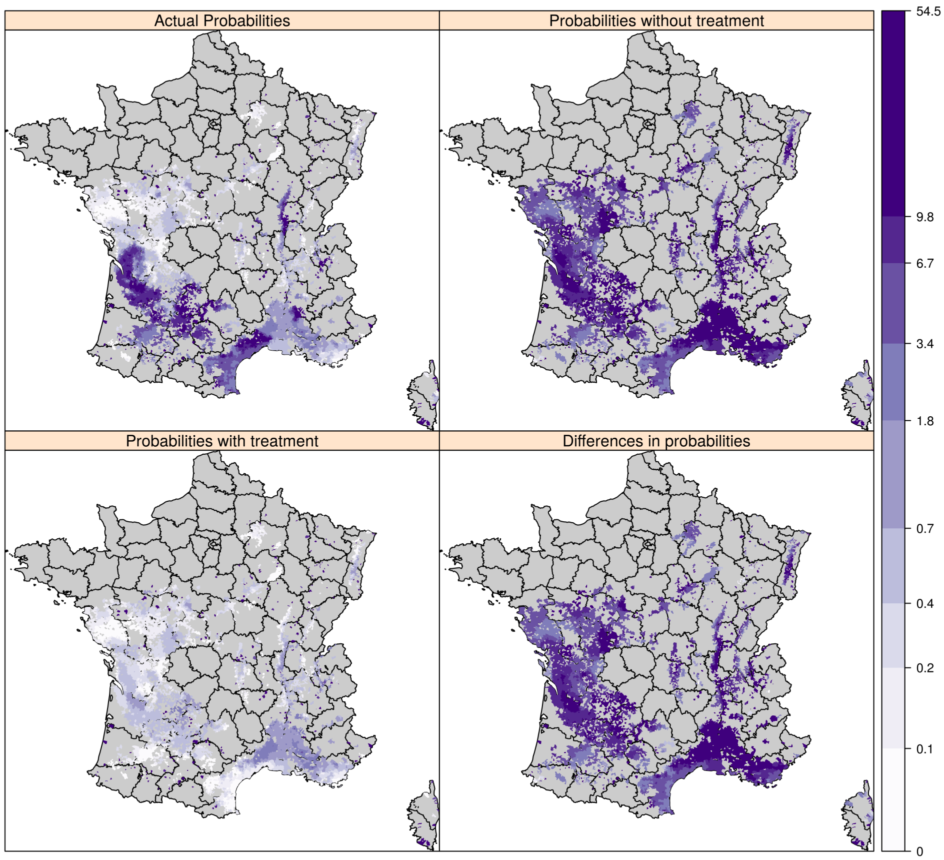
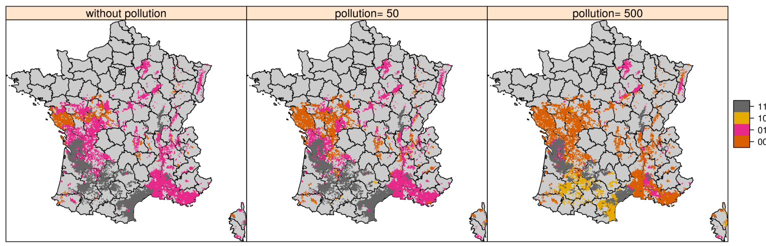


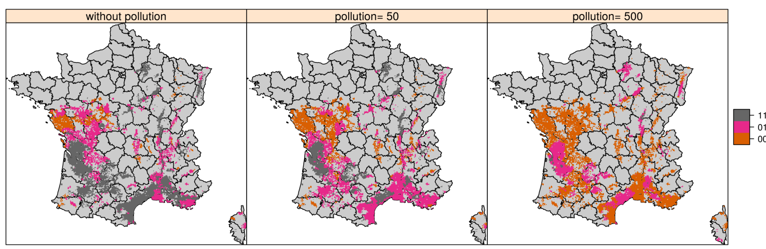
Figure 9: **Spatial concordance between optimum and policy**

Notes: "11" codes the *communes* where the treatment is effective in both cases (acutal policy and social optimum), "00" codes the absence of treatment in both cases, "10" codes the situations where the policy induces treatment which is not socially optimal, and "01" code the situations where the policy induces the abscence of treatment where it is socially optimal to treat. Note that in the case of taxe, the case their are not any *commune* when the actual policy induce a treatment which is not socially optimal. This is simply explained by the fact that in this case only of problem of positive spillovers is not taken into account. The tax allow to internalize fully the negative environmental externalities, and a subsidies scheme should be implemented to internalize the positive externalities.

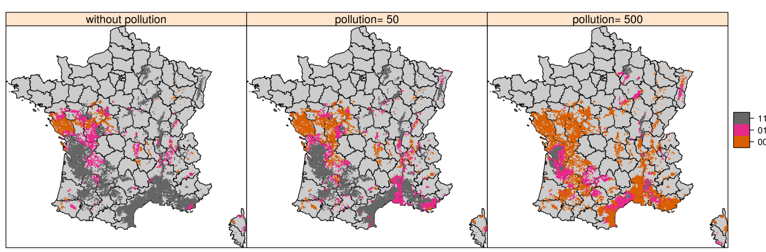
(a) Current policy



(b) Naive anticipations



(c) Myope anticipations



(d) Farseeing anticipations