Title Page (with Author Details)

The Cost of Noncompliance: Evidence from Mandatory Control of a Quarantine Pest in French Vineyards

Jean-Sauveur Ay[*] Estelle Gozlan[†] Emmanuel Paroissien[‡]

August 16, 2022

Abstract

The effectiveness of epidemics control policies is hindered by individual noncompliance. The consequences of such behaviors are not directly assessable from observational data because noncompliance is also driven by individual risk. In this study, we offset the reverse causation bias by leveraging variations in the economic incentives to comply with mandatory insecticide application between French vineyards. We find a high causal effect of noncompliance on the presence of a major epidemic vine disease at the national scale of France. Our benefit-cost analysis shows that decreasing noncompliance could yield large individual and collective benefits as long as the external damages caused by insecticides are not too high.

Acknowledgments We thank the French Ministry of Agriculture for sharing data on FD presence from monitoring efforts resulting from the 2013 policy, official vine acreages, and the number of compulsory treatments within each MCP.

Financial disclosure Financial support for research from the French *Plan National contre le Dépérissement du Vignoble* (PNDV) through a research grant for the RISCA project is also gratefully acknowledged.

Conflict of interest The authors declare no conflict of interest.

Code and data availability We will put all the data gathered for this research and the R code used to derive the full set of results on the INRAE dataverse once the paper is accepted for publication.

[*]CESAER UMR1041, INRAE, Institut Agro, Université Bourgogne Franche-Comté, F-21000, Dijon, France
[†]Université Paris-Saclay, INRAE, AgroParisTech, Paris-Saclay Applied Economics, 91120, Palaiseau, France
[‡]Université Paris-Saclay, INRAE, AgroParisTech, Paris-Saclay Applied Economics, 91120, Palaiseau, France

1 Introduction

Individual self-protection responses to outbreaks of pests and infectious diseases are not always sufficient to control their spread (Costello et al., 2017). The gap between individual motivations and collective outcomes may require coordination of private efforts through coercive policies when collective stakes are high. Such interventions are often designed under the assumption of perfect compliance, but compliance depends on individuals' heterogeneous perceptions and incentives (Funk et al., 2009; Bargain and Aminjonov, 2020). Thus, noncompliance is a pervasive threat to the efficiency of policies.

Yet large-scale evaluations of the effects of noncompliance are scarce in the scientific literature (Shimshack, 2014), principally because of a lack of data due to high monitoring costs and hidden fraudulent individual behaviors (van Rooij and Sokol, 2021). Another key empirical challenge for ex-post policy evaluation is to identify the causal effect of compliance on contaminations. Generally, infection (the outcome) is both caused by noncompliance (the regressor) and a determinant of compliance, as individuals strategically comply when the perceived risk of infection is high. This feedback effect produces a reverse causation bias between the outcome and the regressor in observational (i.e., non-experimental) studies, which poses a threat to the identification of causal effects (Imbens and Wooldridge, 2009; Larsen et al., 2019).

In this article, we overcome this issue by exploiting the features of a recent French program against *Flavescence dorée* (FD), a widespread epidemic disease threatening European vineyards (Tramontini et al., 2020). Using a novel fine-scale data set on pesticide sales, we leverage spatial variations in private incentives to comply (value of potential losses reflected in vineyard prices) to identify the causal impact of noncompliance on the spatial distribution of the disease.

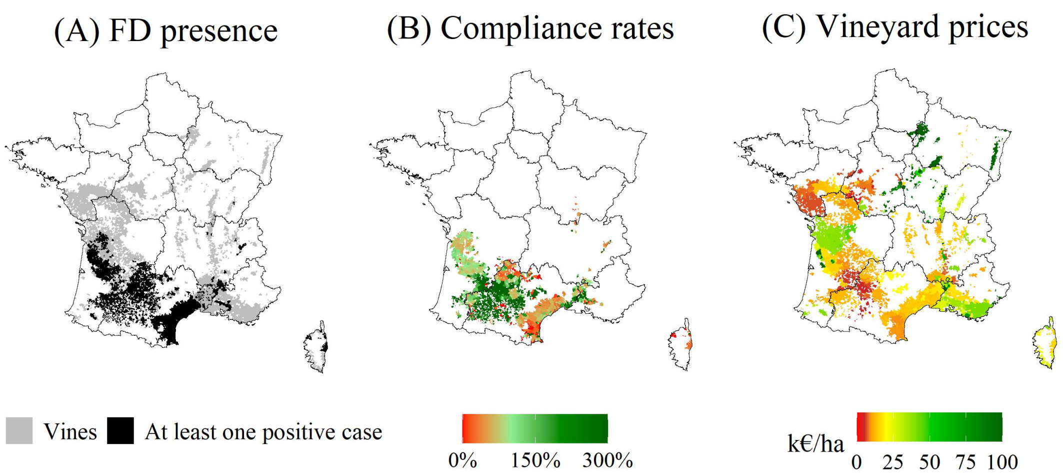
2 Context and data

FD is a severe grapevine epidemic disease which lowers the grape quantity and quality of infected vines, and leads to their death (Chuche and Thiéry, 2014). In France, a large outbreak led to a new ambitious control programin 2013. The French control policy establishes mandatory control perimeters (MCPs) where monitoring and insecticide applications against the vector are mandatory. Each year, the MCPs include all vineyards of municipalities that are adjacent to known FD clusters. Within an MCP, all winegrowers are required to treat their vineyards one to three times yearly using a product approved against the FD vector.

We analyze a dataset merging (i) official data on FD presence, MCP delimitations, and the numbers of mandatory applications at the municipal level from the French Ministry of Agriculture, (ii) newly published data on pesticide sales at the level of postal codes (i.e., groups of 5.6 municipalities on average); and (iii) historical average vineyard prices at the AOC level (see Appendix section A). Mandatory monitoring from the 2013 policy allowed us to finely map the presence of the disease nationally (Fig. 1A). Over 2016–2017, more than 800 municipalities reported at least one FD cluster, accounting for approximately two-thirds of French vineyards.

The raw data available on pesticide sales are aggregated across crops and targets, from a detailed list of products registered at the postal code of the buyers' head offices. We consider six shortlists of the main insecticide products approved for use against the FD vector on grapevines, and show that they all yield similar results. The lists include the $N \in \{10, 15\}$ most used products regionally in postal codes specialized in winegrowing within MCPs. We dropped products that count for more than $\tau \in \{1, 5, 100\}$ percent of the acreage in postal codes without vineyards (see the Appendix Section A). Fig. 1B gives the spatial distribution of compliance rates within MCPs. We obtain national compliance rates which hover around 80%, but these measures are noisy as not all approved products are considered. Our empirical method explicitly accounts for these measurement errors.

Figure 1: Spatial distribution of the main variables



Note: Compliance rates and vineyard prices are truncated at 300% and €100,000/ha, respectively. Compliance rates in panel (B) are computed for municipalities within MCPs with our preferred list ($N = 15$, $\tau = 1$). The data are from 2016. Using the 2017 data and the other shortlists of products lead to similar maps. Panel (C) displays vineyard prices in municipalities with more than 1 ha of vineyards.

Fig. 1C gives the spatial distribution of average vineyard prices. The initial data are available for the 371 French AOCs between 1990 and 2018. Since these precise spatial delineations typically overlap several municipalities, we allocated the AOC-specific prices at the municipal level from their official distribution at the plot level (see Appendix Section A). AOCs are official geographical indications introduced in 1935 to indicate vineyard quality for wine production. The AOC is the main quality signal available to wine buyers and is, consequently, the main driver of both wine and vineyard prices (Ay, 2021; Mérel et al., 2021).

3 Empirical method

We adapt the standard IV estimation method to explicitly account for the measurement errors in the compliance rates, computed using various restricted lists of insecticide products (see Appendix Section B). Our main identifying assumption that price variations across AOC borders are exogenous to the current probability distribution of FD presence. Under this assumption, AOC delineations correlate with FD presence only because they drive winegrowers' compliance with insecticide applications.

The compliance rates C are the ratios of the actually treated acreage A computed from pesticide sales to the acreage S mandated to be treated. Because the measurement error applies to A but not S, we specify the first stage estimation as the regression of A on S, the product between S and the centered natural logarithm of vineyard prices V, and a vector $\mathbf{Q}$ of variables controlling for the drivers of the measurement errors. We expect a larger measurement error on A in less specialized postal codes, where the selected insecticide products are more likely to be used for other crops such as orchards. $\mathbf{Q}$ thus includes the acreages of alternative agricultural land uses, i.e. permanent cropland other than vineyards, annual cropland, and grassland.

$$A = \lambda_0 S + \lambda_1 S \times V + \mathbf{Q}^\top \gamma + \upsilon. \tag{1}$$

Because the logarithm of vineyard price is centered, dividing both sides by S shows that λ_0 and λ_1 are respectively the compliance rate at the average vineyard price and the marginal effect of the logarithm of vineyard price on compliance rates. In the second stage, we set the acreages of alternative land uses to zero ($\mathbf{Q} = \mathbf{0}$) in order project out the measurement errors associated with alternative land uses. We estimate the following linear probability model for the binary variable I indicating FD presence:

$$I = \beta_0 + \beta_1(\hat{\lambda}_0 + \hat{\lambda}_1 V) + \varepsilon. \tag{2}$$

The estimated $\hat{\beta}_1$ measures the causal effect of compliance on FD presence, which is used in the benefit-cost analysis of the text. In both estimation stages, reported standard errors are robust to heteroskedasticity and spatial auto-correlation. In the Appendix Section C, we check that our results are robust to a wide range of robustness checks. In particular, we test alternative estimation methods, including the more classical one-step IV estimator and a large panel of spatial autoregressive models, and design a method to account for imperfect FD monitoring.

4 Results

Effect of vineyard price on compliance Table 1 gives the ordinary least-squares (OLS) estimates of the regression of the actually treated acreage (computed from insecticide sales) on (i) the acreage to treat according to the MCPs of the FD control policy, (ii) the interaction between this acreage to mandatory treat and the centered logarithm of vineyard price, and (iii) the shares of acreage in alternative land uses. We ran this regression for the six different lists of insecticide products, for all postal codes in the MCPs pooled over the 2016–2017 period.

All the estimated coefficients in Table 1 are of the expected signs, with R^2 ranging from .75 to .81. The coefficients in the first row give the average compliance rate at the average vineyard price after controlling for measurement errors from alternative uses of insecticide products. They range from 55% to 73% depending on the product list considered. The third row shows that a 10% increase in vineyard price raises the average compliance rate by 1.3 to 2.1 percentage points. For all six regressions, the vineyard price instrument is strong according to the usual Fisher statistics. Also expected, alternative insecticide uses cause the treated acreages to increase with the proportion of annual crops and other permanent crops, and to decrease with the proportion of grassland.

The strong effect of the price instrument on compliance rates is robust across all product lists. Intuitively, the average compliance rate increases with the number of selected products N and when the specificity parameter τ decreases (when the less vine-specific products are dropped from the restricted lists). In the Appendix Section C, we show that these first stage results are also robust to the inclusion of other control variables including landscape, climate, grape varieties, and agricultural structures.

Table 1: First-stage OLS regressions about the determinants of compliance rates

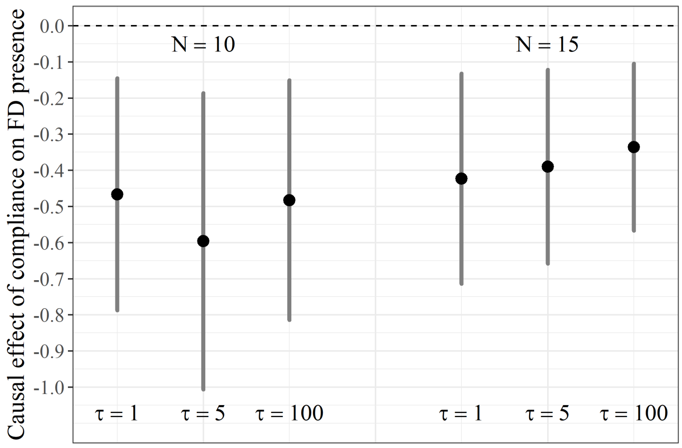
	Outcome: acreage actually treated against the FD vector					
	$N = 10$			$N = 15$		
	$\tau = 1$	$\tau = 5$	$\tau = 100$	$\tau = 1$	$\tau = 5$	$\tau = 100$
Acreage to treat (ATT)	0.573***	0.565***	0.579***	0.677***	0.714***	0.730***
	(0.019)	(0.022)	(0.022)	(0.023)	(0.026)	(0.025)
ATT × log. price deviation	0.167***	0.130***	0.148***	0.191***	0.198***	0.218***
	(0.028)	(0.033)	(0.032)	(0.034)	(0.039)	(0.037)
Share in permanent crops	1.130***	1.509***	2.269***	1.512***	2.023***	2.751***
	(0.257)	(0.325)	(0.287)	(0.331)	(0.376)	(0.319)
Share in annual crops	0.052***	0.107***	0.105***	0.085***	0.172***	0.169***
	(0.010)	(0.015)	(0.015)	(0.013)	(0.017)	(0.016)
Share in grasslands	-0.029***	-0.045***	-0.030***	-0.041***	-0.056***	-0.045***
	(0.012)	(0.013)	(0.013)	(0.014)	(0.016)	(0.015)
Observations	1,586	1,586	1,586	1,586	1,586	1,586
R-squared	0.804	0.746	0.760	0.804	0.782	0.797
F-stat for weak instrument	35.80	36.08	33.92	42.28	39.82	40.86

Notes: All regressions pool data from 2016 and 2017, with year and region as fixed effects. Standard errors in parentheses and F-statistics for weak instruments are corrected for spatial autocorrelation as presented in Appendix Section B.

Causal effect of compliance The second stage consists in regressing the FD presence on the compliance rates predicted only by the instrument. Fig. 2 gives the OLS estimates of these second stages with a linear probability specification of FD presence. For all lists of insecticide products, we find that increasing the compliance rate significantly lowers the probability of FD presence. The point estimates of the causal effect range from $-.6$ to $-.34$. They are higher in absolute value with smaller N regardless of the specificity parameter τ. We obtain relatively wide robust 95% confidence intervals, a common feature of IV methods as they favor consistency over efficiency. Taken together, the reported confidence intervals span values from -1 to $-.1$ with a preferred median estimate of $-.45$, which suggests that increasing compliance by 10 points would reduce the probability of FD presence by 4.5 points. In the Appendix Section C, we show that the estimated coefficients are remarkably stable across more than 60 alternative specifications, with point estimates of the causal effects of compliance on FD presence ranging from $-.6$ to $-.3$.

Benefits from increasing compliance Vine plants infected by FD must be replaced for production to resume. Because new plants mature only after a few years, the cost of an FD contamination can be approximated by a given number of years of production loss. Following the Ricardian approach (Mendelsohn et al., 1994), we consider that current vineyard prices V are the sums of the expected annual returns $R/(1+r)$ over the future periods discounted by a rate $r > 0$ (Ay and Gozlan, 2020). The expected annual return from wine production is $R = r \times V$. Because all infected plants must legally be replaced, we consider that an infection causes a production loss over k years. If noncompliance increases the probability of infection by Δp. The resulting expected per ha cost is:

Figure 2: Causal effect of compliance from second-stage OLS regressions



Note: All estimations were conducted on the 1,586 postal codes as in the first stages. The confidence intervals are built using standard errors accounting for spatial autocorrelation (Appendix Section B).

$$\Delta p \sum_{s=1}^{k} R/(1+r)^s = \Delta p \times V[1-(1+r)^{-k}]. \tag{3}$$

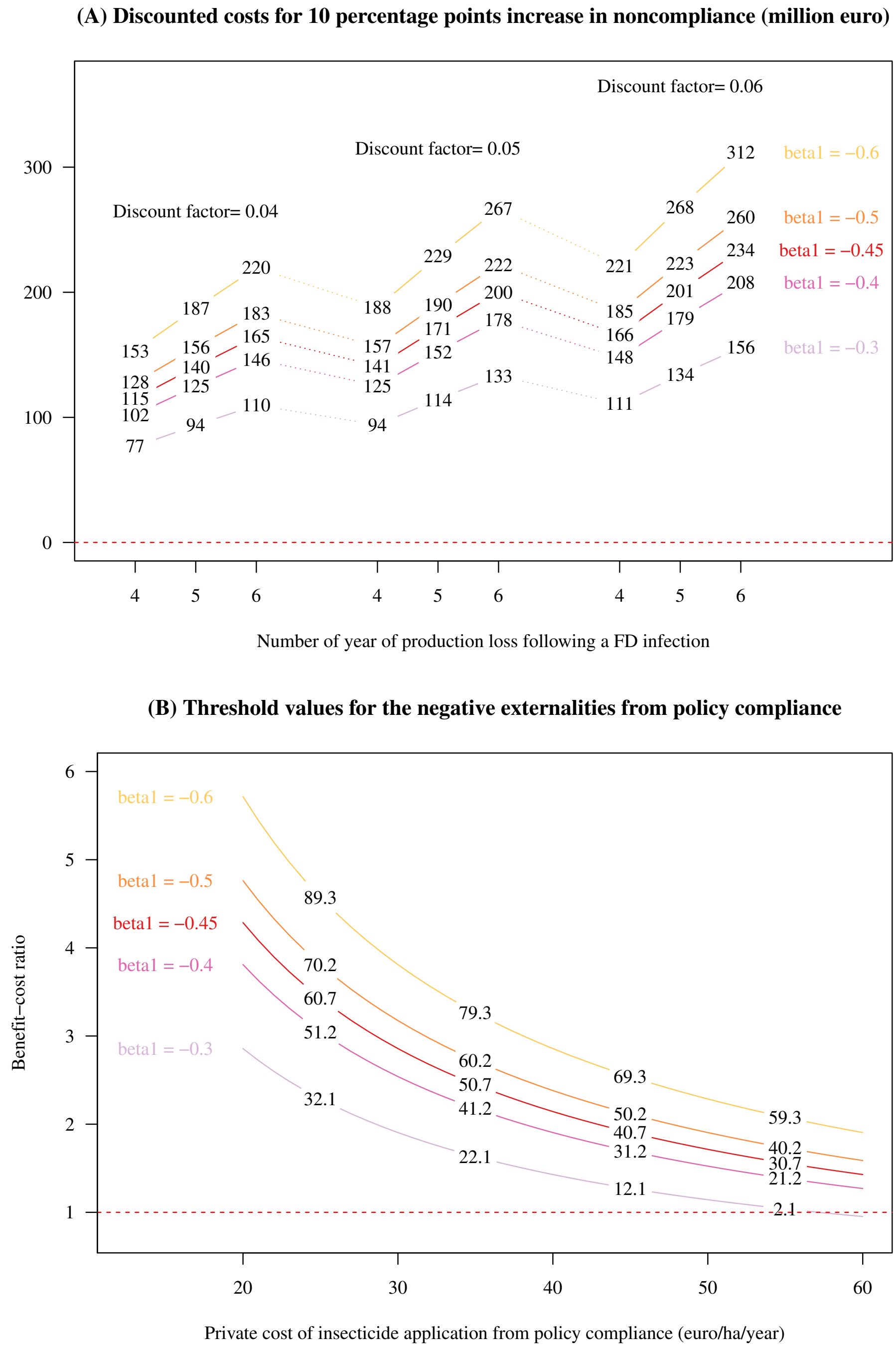
Our median calibration is r=5% and k=5.[1] Nationally, vineyard acreage within MCPs comprises about 550,000 ha, with an average vineyard price of €32,000/ha that yields an average return of €1,600/ha/year. Fig. 3A shows the expected benefits from a 10-point increase in the average compliance rate, considering that FD presence in a given municipality is a risk to all its vineyards.

Our preferred causal estimate combined with the median calibration suggests that this 10-point increase in compliance corresponds to a total expected discounted benefit of €171 million (€15.5/ha/year). This suggests that noncompliance with mandatory pest control causes a high economic cost due to avoidable infections and production losses. This result is robust over a plausible range of values for the discount factor and the number of years of production losses following a contamination. We provide a more detailed economic evaluation in Appendix Section D including the spreading dynamics of the disease inside a postal code, the role of monitoring efforts, and the replacement costs. Calibrations of this more extended model suggests the above calculations underestimate the cost of noncompliance.

Benefit-cost analysis Pushing these calculations further, we compare these estimated benefits with the private costs of compliance. For a total area to treat of about 1 million ha (550,000 ha of vineyard within MCPs multiplied by an average number of yearly treatments around 2), we consider an average cost for one insecticide application of €35/ha (which includes both the cost of purchasing the insecticide product and the cost of applying it). Increasing overall compliance by 10 points would therefore cost an additional €3.5 million of private expense annually. Keeping the discount factor at 5%, the corresponding discounted cost of the 10-point increase of the average

[1] Once a plant is replaced, wine-growers have to wait at least 3 years to produce wine, and we add 2 more years because of poor yields and quality from young plants.

Figure 3: Economic evaluation of noncompliance with pest control policy



Note: Our estimate of €171 million reported in the text corresponds to five years of production loss and a discount factor of 5% in panel (A). For this preferred set of parameters, panel (B) displays the threshold values for external damages above which increasing compliance is not socially welfare improving.

compliance rate is €70 million. Compared with the expected benefits computed above, the benefit-cost ratio of increasing compliance is 171/70= 2.45. Fig. 3B shows the sensitivity of this value to the causal effect and to the private cost of compliance. The benefit-cost ratio increases sharply for smaller values of costs and higher effects of compliance. The ratio is always greater than 1, except for the combination of extremely conservative values.

The total cost of noncompliance includes the environmental and health impacts of insecticides. Our results imply a threshold value for these damages under which increasing compliance improves total social welfare. If health and environmental damages are lower than the difference between the total benefits from decreasing FD presence and the private cost of compliance for winegrowers, more compliance is socially desirable. This leads to a threshold value of 171–70= €101 million for the discounted damages, or €5.05 million annually with a 5% rate. Combined with the total acreage to treat of 1 million ha by year, this suggests that increasing compliance would be detrimental to society if the external damage associated with the mandatory insecticide application is larger than about €50/ha/year. Fig. 3B shows the sensitivity of this threshold to the value of the causal effect and the private cost of treatment.

Discussion

Mandatory insecticide treatments may seem at odds with the public health and environmental objectives to decrease pesticide use, due to widespread evidence of residues (Tang et al., 2021) and growing knowledge about their hidden damages (Beketov et al., 2013; Larsen et al., 2017; Lai, 2017; Taylor, 2020) Despite the growing importance of this issue, comprehensive cost-benefit assessments of pesticides use remain elusive. In France, a 2021 report BASIC (2021) evaluates the direct costs of pesticide use (water quality, greenhouse gases, and professional diseases) at €340 million, and the indirect costs (biodiversity and all human diseases) at €6,216 million. Dividing these aggregate costs by the 19.15 million ha of agricultural used area (excluding grassland, with only 6% of permanent crops) frames the total cost of all pesticides across all crops in France between €17/ha and €335/ha, to be compared to our threshold of €50/ha only for insecticide applications targeting the FD disease that is quite close to the lower bound. On the benefits side, several studies suggest that significant cuts in pesticide use (ranging from 30% to 50%) would have only small consequences on agricultural yields or profits (Jacquet et al., 2011; Hossard et al., 2014; Lechenet et al., 2017). Although we do not estimate externality costs, our results contribute to document maximum values allowing for economically sound policies. Our case study, based on large-scale observational data and addressing the reverse causation bias, shows that noncompliance contributes to spread a disease at a large scale. This results in high economic losses and may further extend the duration of mandatory treatments.

References

Ay, J.-S. (2021). The informational content of geographical indications. *American Journal of Agricultural Economics 103*, 523–542.

Ay, J.-S. and E. Gozlan (2020). Disease dispersion as a spatial interaction: The case of flavescence dorée. *Natural Resource Modeling 33*, e12265.

Bargain, O. and U. Aminjonov (2020). Trust and compliance to public health policies in times of COVID-19. *Journal of Public Economics 192*, 104316.

BASIC (2021). Analyse de la création de valeur et des coûts cachés des pesticides de synthèse. Technical report, https://lebasic.com/wp-content/uploads/2021/11/BASIC_Etude-Creation-de-Valeur-et-Couts-Societaux-Pesticides_20211125.pdf, last assessed the january, 24th 2022.

Beketov, M. A., B. J. Kefford, R. B. Schäfer, and M. Liess (2013). Pesticides reduce regional biodiversity of stream invertebrates. *Proceedings of the National Academy of Sciences 110*(27), 11039–11043.

Chuche, J. and D. Thiéry (2014). Biology and ecology of the flavescence dorée vector scaphoideus titanus: a review. *Agronomy for Sustainable Development 34*(2), 381–403.

Costello, C., N. Querou, and A. Tomini (2017). Private eradication of mobile public bads. *European Economic Review 94*, 23–44.

Funk, S., E. Gilad, C. Watkins, and V. A. Jansen (2009). The spread of awareness and its impact on epidemic outbreaks. *Proceedings of the National Academy of Sciences 106*(16), 6872–6877.

Hossard, L., A. Philibert, M. Bertrand, C. Colnenne-David, P. Debaeke, N. Munier-Jolain, M.-H. Jeuffroy, G. Richard, and D. Makowski (2014). Effects of halving pesticide use on wheat production. *Scientific Reports 4*(1), 1–7.

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

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

Lai, W. (2017). Pesticide use and health outcomes: Evidence from agricultural water pollution in China. *Journal of Environmental Economics and Management 86*, 93–120.

Larsen, A. E., S. D. Gaines, and O. Deschênes (2017). Agricultural pesticide use and adverse birth outcomes in the San Joaquin Valley of California. *Nature Communications 8*(1), 1–9.

Larsen, A. E., K. Meng, and B. E. Kendall (2019). Causal analysis in control–impact ecological studies with observational data. *Methods in Ecology and Evolution 10*(7), 924–934.

Lechenet, M., F. Dessaint, G. Py, D. Makowski, and N. Munier-Jolain (2017). Reducing pesticide use while preserving crop productivity and profitability on arable farms. *Nature Plants 3*(3), 1–6.

Mendelsohn, R., W. D. Nordhaus, and D. Shaw (1994). The impact of global warming on agriculture: A Ricardian analysis. *American Economic Review 84*(4), 753–771.

Mérel, P., A. Ortiz-Bobea, and E. Paroissien (2021). How big is the "lemons" problem? Historical evidence from french wines. *European Economic Review 138*, 103824.

Shimshack, J. P. (2014). The economics of environmental monitoring and enforcement: A review. *Annual Review of Resource Economics 6*, 339–60.

Tang, F. H. M., M. Lenzen, A. McBratney, and F. Maggi (2021). Risk of pesticide pollution at the global scale. *Nature Geoscience 14*(4), 206–210.

Taylor, C. A. (2020). The cicada song: The impact of insecticides on infant health and long-term outcomes. CEEP Working Paper Series.

Tramontini, S., A. Delbianco, and S. Vos (2020). Pest survey card on flavescence dorée phytoplasma and its vector scaphoideus titanus. *EFSA Supporting Publications 17*(8), 1909E.

van Rooij, B. and D. D. Sokol (2021). *The Cambridge Handbook of Compliance*. Cambridge University Press.

The Cost of Noncompliance: Evidence from Mandatory Control of a Quarantine Pest in French Vineyards Supplementary Information

August 16, 2022

Contents

List of Figures

List of Tables

A Data construction

We assemble a data set at the postal code level ($N = 6,300$) from several sources. This section describes the sources, and how we build the variables used in the main text. Table A.1 in this supplementary information file reports the summary statistics of all data gathered.

A.1 Sources

FD presence and 2013 control policy. The French Ministry of Agriculture provided us with a data set at the municipal level ($N = 35,300$) for the period 2013–2017 containing (i) the presence of FD, (ii) the vineyard acreages in 2012, (iii) the number of mandatory insecticide applications according to the control policy, and (iv) the share of monitored acreage (used in Section C). Because of a methodological change in 2015, FD presence and monitoring variables are only usable for the years 2016 and 2017. The number of annual treatments varies from zero to three, depending on the proximity to the FD cluster and the local knowledge from experts. We aggregate these data at the postal code level (i.e., groups of 5.6 municipalities on average) for each year to obtain the total vineyard acreage to treat, a dummy variable indicating FD presence, and the share of monitored vineyards.

Vineyard prices. We built the vector of vineyard price by combining two sources. First, we collected for each year between 1995 and 2017 the average price for each *appellation d'origine contrôlée* (AOC, $N = 371$) from the website of the French Ministry of Agriculture (`https://www.agreste.agriculture.gouv.fr`). Second, we matched these prices with the map of AOCs produced by the French *Institut National des Appellations d'Origine* (INAO), available at `https://www.geoportail.gouv.fr`. AOC delineations date from 2020, but most of them were created in the early 20th century. The price proxy at the postal code level is given by the average of the AOC prices weighted by the surface of each AOC in each municipality within each postal code.

Insecticide sales. The data on insecticide sales were recently made available by the French water agency (*Agence de l'eau*) at the website `https://www.data.eaufrance.fr`. They provide the total quantities purchased of each certified product for each year between 2013 and 2018. They are georeferenced at the postal code level of the buyer's head office. Using recommended dosages and the period of officially approved use available at the ANSES website (`www.anses.fr`), these data allow to compute the acreages *actually* treated against FD in each postal code in 2016 and 2017. To do so, we need to identify the products mainly and specifically used to against the FD vector. The next Section A.2 presents our strategy to address this issue.

Control variables. We use data from the 2010 French agricultural census (`https://www.agreste.agriculture.gouv.fr`), initially available at the municipal level, to build the land use variables (noted $\boldsymbol{X}$ in Section B hereafter). We also collect additional data to build control variables and assess the robustness of our causal results to these potential counfounders. From the same 2010 census data, we compute the number of wine farms, the mean acreage of each wine farm, the number of workers in wine farms, the number of workers by acreage in wine farms, and the average gross margin for each wine farm at the postal code level. From the 2018 Corine Land Cover data (available at `https://land.copernicus.eu/pan-european/corine-land-cover`), we compute the mean size of vineyard plots, the share of semi-natural acreages, the landscape shape index, and the Shannon diversity index for each postal code. Because all grape varieties are not equally threatened by FD (Eveillard et al., 2016) and because the choices of grape varieties are legally constrained within AOCs, we merge for each postal code the percentage of the AOCs that allow the main 9 French grape varieties. Lastly, we use municipal data from Météo-France to compute average climate variables. From the 1990-2010 period, we average maximum temperature, cumulative precipitations, number of rainy days, solar radiation, wind speed, relative humidity, number of freezing cold days, and evapotranspiration to control the effect of climate on FD presence. Figure A.1 gives the correlation matrix between these control variables.

A.2 Products selection

The French Agency ANSES has provided us with the list the all insecticide products allowed over our study period for aerial application on vines against the leafhopper carrying the FD.[1] The sale data counts 108 of these products over the period 2016–2017.

Most of these products have multiple purposes. They can be used to target other insects threatening vines, and to target similar insects for other crops. This is a source of measurement error in our estimations of the treated areas, and in turn, in the compliance rates. Our strategy to mitigate these errors is to select the products which are *mostly* used against the FD vector among the full list of officially approved products. Specifically, we select the N products for which the quantities purchased can be used to treat the largest areas in postal codes specialized in vines within MCPs. We define the specialized postal codes as those where the share of vines in the Utilized Agricultural Area (UAA) is larger than s_u. We do not include permanent grasslands in the UAA because these acreages generally do not receive any insecticide treatments. We consider the threshold $s_u = 70\%$, so that 183 postal codes within MCPs are considered as specialized in vineyards nationally. The conversion from the quantity purchased into actually treated areas relies on the recommended dosage from ANSES. For each product, year, and postal code, we compute the area that could be sprayed using all the quantity purchased at the recommended dosage.

Although we consider only the products that are approved specifically against leafhoppers in vines, and then only select the products that are intensively used within highly specialized postal codes within MCPs, this strategy may not convincingly eliminate the risk of including irrelevant products. In particular, if one product is only *partly* used against the FD vector, and partly used for another purpose, including either all or none of its quantity purchased would lead to a measurement error in the compliance rate (either upward or downward).[2] This is because the data do not discriminate across uses made of each insecticide purchase. Another key issue is to exclude the products that are not used specifically against the FD vector. To do so, we investigate whether each product is significantly used in areas with few (if any) vineyards. In these postal codes, the purchased products cannot be used against the FD vector because it is specific to vines. We define the postal codes without vines as those where the share of vines in the UAA excluding grasslands is below s_l with $s_l = 0.1\%$. About 4,000 postal codes (63.5%) are considered without vineyards.

Lastly, we account for the heterogeneity across regions in the choice of products. If winegrowers in

[1]The data indicates the species of leafhopper against which each product has been proven effective. We keep only the products approved against *Scaphoideus titanus*, which carries the FD disease. We remove products only approved against *Empoasca vitis*, which is not proven to carry the FD disease.

[2]This issue is similar to that of a type II error, while the corresponding type I error would be to exclude a product used against the FD vector. No strategy can guarantee a zero risk for both type I and type II errors.

different regions use different insecticide products against the FD vector, then a selection strategy based solely on national aggregates may not select the major products in each region. To address this issue, we consider region-specific lists of products. We delineate four broad wine regions containing the main French vineyards affected by the FD disease: Aquitaine which contains the Bordeaux vineyards, Occitanie in the southern France, Bourgogne-Auvergne that lies from Burgundy down to the the north of the Rhône valley, and PACA-Corse at the south-eastern corner. Fig. A.2 below shows the regional rankings of the top 30 products according to their actual treated area in the specialized postal codes. The dotted curve gives the cumulative share of the total area that can be treated with all the 108 approved products. It shows that considering only the top $N = 15$ products captures most of the quantity used in specialized postal codes, between 84% in Occitanie up to 97% in Burgundy. This supports our strategy of using shortlists of products regionally.

For each insecticide product on the x-axis if Fig. A.2, the green (resp. red) bar indicates the ratio between the actual treated area and the total UAA without grassland among specialized postal codes (resp. postal codes without vines) on the scale of the y-axis. In most cases, the top 30 products selected in each region are not significantly used in postal codes without vines. Panels (a) to (c) provide reassuring evidence that the products with the largest actually treated areas in specialized postal codes are mostly specific to the FD vector, and only marginally used on other crops than vines. The higher red bars in Panel (d) indicate that some selected products in south-eastern France are often used in areas without vines (e.g., Klartan). It suggests that the products selected in this region are also used on other crops, such as orchards, which are extensively cultivated in this part of France.

Although most selected products are marginally used in postal codes without vines, we find some products that are significantly used both in specialized postal codes and in postal codes without vines. Including them would overestimate compliance rates, but excluding them would lead to underestimating it. To evaluate the salience of this issue, we proceed to a sensitivity analysis. We consider different lists of the top $N \in \{10, 15\}$ products mostly used in specialized postal codes, after removing all products for which the ratio between the treated area and the UAA in postal codes without vines is greater than $\tau \in \{1, 5, 100\}$. Setting $\tau \in 100$ leads to considering the top N products in specialized postal codes, regardless of how they are used in postal codes without vines.

These parameters yield six lists of products leading to six proxies of the area actually treated against the FD vector in each postal code. Our estimation of the compliance rates is the ratio between this actually treated area and the acreage to treat, which is the product between the acreage in vines and the number of mandatory treatments from the control policy within MCPs. As expected, setting $N = 10$ instead of $N = 15$, or $\tau = 1\%$ instead of $\tau = 100\%$, yields slightly smaller values for compliance rates. These parameters yield lists with fewer products, which increases the likelihood of underestimating the true compliance rate but decreases the likelihood of overestimating it. Depending on the postal code, the bias may be positive for all compliance rates, negative for all of them, or positive for some and negative for others. Our identifying assumption only requires the measurement error not to be systematically correlated with vineyard price, after controlling for the shares of alternative agricultural land uses as presented more formally in Section B below.

B Econometric framework

System of equations. We note I^* the binary variable equals to one if *Flavescence dorée* (FD) is present in a postal code within a Mandatory Control Perimeter (MCP) and zero if not. We consider a linear probability model for the effect of the compliance rate C^* on FD presence:

$$I^* = \beta_0 + \beta_1 C^* + \epsilon. \tag{B.1}$$

The causal parameter of interest is β_1, measuring the effect of compliance on FD presence, as an indicator about the effectiveness of the control policy. We expect $\beta_1 < 0$, as insecticide application would decrease FD presence through the regulation of its vector. Hence, vine growers face a trade-off between the cost of insecticide application and the benefit they expect from decreasing the risk of a FD contamination. Under constant marginal cost of insecticide application, effective compliance depends both on the exposure to the infection and on the loss from an infection. As the FD disease is incurable, we proxy the discounted value of the loss by the average per-ha vineyard price V for each postal code. We consider the linear projection of C^* on I^* and V:

$$C^* = \alpha_0 + \alpha_1 I^* + \alpha_2 V + \eta \quad \text{with} \quad \mathbb{E}(\eta \mid I^*, V) = 0. \tag{B.2}$$

We expect $\alpha_1, \alpha_2 > 0$ because a high exposure and a high loss from an infection provide more incentives for wine-growers to comply. Without loss of generality, the error term η is mean-independent in equation (B.2) because it is a descriptive relationship (i.e., a linear projection) without a causal meaning. However, the dependence from I^* to C^* in equation (B.2) implies that the compliance rate C^* is endogenous in equation (B.1) and, consequently, the ordinary least squares (OLS) estimator of β_1 is inconsistent. This reverse causation bias stems from the strategic compliance of wine producers. It leads to a spurious correlation between the compliance rates and the errors of the linear probability model (B.1) and a downward bias from an OLS estimation (Frisvold, 2019). Controlling for V in equation (B.1) is not relevant as long as $\mathbb{E}(C^*\epsilon \mid V) = \frac{\alpha_1}{1-\alpha_1\beta_1}\mathbb{E}(\epsilon^2 \mid V) \neq 0$.

Instrumental variable (IV) strategy. We rely on an IV strategy using V as an instrument to identify the causal parameter of interest β_1. This requires the classical IV conditions of instrument relevance $H_{IV1} : |\alpha_2| >> 0$ and instrument exogeneity $H_{IV2} : \mathbb{C}(V, \epsilon) = \mathbb{E}(V\epsilon) = 0$. The first assumption is theoretically motivated by the strategic behavior of wine growers presented above, and is empirically assessed by the Fisher statistics on the significance of V in the reduced form of equation (B.2). The second assumption H_{IV2} is justified by the historical pre-determination of AOC delineations that pre-exist FD presence and hence are not influenced by the current risk of FD infection. This assumption also prohibits any correlation between vineyard prices and unobserved determinants of FD presence, which is achieved by adding control variables in the empirical models. Under $H_{IV} = H_{IV1} \cap H_{IV2}$, vineyard prices are correlated to FD presence only through their influence on compliance rates, and the IV estimator of β_1 is asymptotically consistent:

$$\hat{\beta}_1^{IV} = \frac{\mathbb{C}(I^*, V)}{\mathbb{C}(C^*, V)} \xrightarrow[H_{IV}]{p} \beta_1. \tag{B.3}$$

Measurement errors. This IV-based identification strategy is challenged by the imperfect measurement of compliance rates estimated from insecticide sales that are aggregated across crops and targeted pests. For each list of products presented in Section A.2 above, we observe $C = C^* + \mu$ instead of C^*, where μ denotes the measurement error due to the alternative uses (alternative crops or alternative targets) of the insecticides approved against the FD vector. Replacing C^* by C in the IV estimator of equation (B.3) provides a consistent estimator of β_1 only if vineyard prices are uncorrelated with the measurement errors, that is, $\mathbb{C}(V, \mu) = 0$. This is unlikely to be true as we expect locations with a smaller share of vines to exhibit both a lower vineyard price V (because prices drive specialization) and a higher measurement error μ (because of higher share of alternative land uses). To circumvent this problem, we model the measurement error by $\mu = \gamma_0 + \boldsymbol{X}^\top \boldsymbol{\gamma} + \xi$, where $\boldsymbol{X}$ is the vector of acreages of the alternative agricultural land uses divided by the acreage to treat, and ξ is the residual measurement error assumed to be uncorrelated with vineyard price, $H_{ME} : \mathbb{C}(V, \xi) = 0$. This specification amounts to considering a constant application rate for each land use and each target, as it is typically required from technical information of pesticide products.[3] The residual measurement error ξ comes from the storage of insecticides, the random variations of weather, or any other short-run determinant of insecticide application (for which we conduct a robustness check by analyzing two consecutive years, i.e., 2016 and 2017). Our measure C of the compliance rates can then be written as:

$$C = \lambda_0 + \lambda_1 V + \boldsymbol{X}^\top \boldsymbol{\gamma} + \zeta \tag{B.4}$$

with $\lambda_0 = \gamma_0 + \frac{\alpha_0 + \alpha_1 \beta_0}{1 - \alpha_1 \beta_1}$, $\lambda_1 = \frac{\alpha_2}{1 - \alpha_1 \beta_1}$, and $\zeta = \xi + \frac{\alpha_1 \epsilon + \eta}{1 - \alpha_1 \beta_1}$. Under $H_{2SLS} = H_{IV} \cap H_{ME}$, we have $\mathbb{C}(V, \zeta) = 0$ so that the price V is exogenous in equation (B.4) and the coefficient λ_1 can be consistently estimated by OLS. Note that the measurement error on the compliance rate $C = A/S$ mostly stems from our proxy on the acreage potentially treated A, as we precisely measure the area to treat S. This generates a skewness in the distribution of ζ.[4] We expect $H_V : \mathbb{V}(\zeta) = \sigma^2/S^2$ and account for this heteroskedasticity by multiplying equation (B.4) by S before the estimation. This yields equation (1) in the Materials and Methods, where A is explained by S, $V \times S$, and $\boldsymbol{Q} = \boldsymbol{X} \times S$. Under H_V, our OLS estimation of this equation reported in Table 1 of the main text (using different lists of insecticide products) is the efficient generalized least squares (GLS) estimator of equation (B.4). Another appealing property from this specification of measurement errors comes from the possibility to set $\boldsymbol{X} = \boldsymbol{0}$ to predict compliance rates in the second stage. This amounts to projecting out the measurement errors associated with alternative land uses. It follows that a simple regression of I^* on the predicted compliance rates from equation (B.4) with $\boldsymbol{X} = \boldsymbol{0}$ yields an asymptotically consistent estimator under H_{2SLS}:

$$\hat{\beta}_1^{2SLS} = \frac{\mathbb{C}(I^*, \hat{\lambda}_1 V)}{\mathbb{V}(\hat{\lambda}_1 V)} = \frac{\mathbb{C}(I^*, V)}{\hat{\lambda}_1 \mathbb{V}(V)} \xrightarrow[H_{2SLS}]{p} \beta_1. \tag{B.5}$$

Figure 3 in the main text reports estimates of $\hat{\beta}_1^{2SLS}$ for various lists of approved products. The confidence intervals (CIs) are obtained using Conley-type Heteroskedastic and Autocorrelation Consistent (HAC) variance matrices which account for spatial dependence of the residuals across neighboring locations (see Section C). Bootstrap methods accounting for the fact that we cannot recover the structural errors ϵ yield similar CIs.

[3] Without loss of generality, consider a unique insecticide product and 2 alternative land uses. Under constant application rates, the volume of sales (in physical units) is $T = (\tau C^* + \tau_0)S + \tau_1 Q_1 + \tau_2 Q_2$ where τ is the recommended dosage against the FD, τ_0 is the dosage for other insects on the vineyards area S, and τ_1 and τ_2 are the respective dosages from the land uses 1 and 2. Our estimation of compliance rate is $C = T/(\tau S) = C^* + \tau_0/\tau + (\tau_1/\tau)X_1 + (\tau_2/\tau)X_2$, which corresponds to our specification because $X_k \equiv Q_k/S$.

[4] This is because the measurement error on A from alternative land uses and from idiosyncratic unobserved shocks are both divided by S.

C Robustness checks

We perform an extensive sensitivity analysis to assess the dependence of our causal evidence to the presence of unobserved confounders, spatial autocorrelation, and imperfect monitoring. Our main result, i.e. the large causal effect of noncompliance on FD presence, is preserved among the full range of extended models presented in this Section. This is illustrated by the specification chart in Figure C.1.

C.1 Accounting for potential confounders

As presented in Section B of SI, the validity of the instrument relies on $H_{IV1} : |\alpha_2| >> 0$, which is directly testable from the first stage of the 2SLS estimation. Figure C.2 displays the marginal effect of vineyard price on compliance rates with a partial residual plot. It illustrates the highly significant linear relationship between the instrument and the endogenous explanatory variable.

The IV identification also relies on $H_{IV2} : \mathbb{E}(V\epsilon) = 0$, the absence of correlation between vineyard prices and the unobserved determinants of FD presence. This assumption cannot be directly tested (as ϵ is not observable) but we introduce three sets of control variables that could determine FD presence and be incidentally correlated with vineyard price. These variables are related to (i) landscape and agricultural structures, (ii) average climate, and (iii) grape varieties. Tables C.1, C.2, C.3 show that including these additional control variables does not qualitatively affect our results.

Table C.1 first reports the 2SLS estimates with the control variables (i). Elevation, semi-natural area, and number of wine farms impact negatively compliance, while the impact of farms' size is positive. For the probability of FD presence, elevation and semi-natural area have negative effects, the Shannon diversity index, the number of wine farms and their size have positive effects.

Table C.2 then provides the 2SLS estimates with the control variables (ii) with second-order polynomials of centered values to account for non linearities of average temperature and cumulative precipitations. In both stages, compliance and FD presence are negatively impacted by temperature and precipitations and the terms of second-order are all significant at 95%.

Table C.3 finally gives the 2SLS estimates with the control variables (iii). Almost all Grape varieties determine of both compliance and FD presence, and their effects are consistent with laboratory results (Eveillard et al., 2016). Red varieties such as Pinot N., Gamay, Merlot, Grenache are less threatened by FD, contrary to vulnerable varieties such as Cabernet franc and Chardonnay.

Vineyard price remains a strong instrument for compliance in all specifications. We cannot include all these control variables simultaneously because it would induce a loss of degree of freedom, which decreases the strength of our instrument (producing bias) and increases the standard errors of the coefficients (decreasing precision).

Lastly, we propose to control for the spatial lags of the instrument. This allows to take into account potential spatial confounders without observing them (local growing practices, professional advising structures, or other contextual effects for instance). Table C.4 and C.5 give the 2SLS estimates with spatially-lagged vineyard prices respectively computed from 10 km buffers and 5th order contiguity (we have testes other spatial schedules that we do not report here). In most specifications, the spatial lag of the spatial lag is significant in the first stage about compliance rates but not significant in the second stages about FD presence. The causal effects are still robust to these controls, which supports the assumption of a null correlation between vineyard prices and the unobserved determinants of FD presence.

C.2 Accounting for spatial autocorrelation of FD presence

Even without unobserved confounders, the spreading patterns of FD can produce a spatial autocorrelation of FD presence that could bias our IV results (Ay and Gozlan, 2020). FD presence at the postal code level is unlikely to present a contemporary spatial autocorrelation because of the small annual dispersing ability of the vector (at most 500 meters by year, see Tramontini et al., 2020). But, in the long run, neighboring postal codes might have similar probabilities of FD presence and similar vineyard prices (regardless of their levels of compliance). We account for this possibility by estimating spatial econometric models, which include the spatially lagged value of FD presence as an additional control variable. Because of error propagation, the standard IV and 2SLS estimation procedures are no longer convergent for such specifications. Hence, we use the generalized method of moment estimator of Kelejian and Prucha (1998, 2010). For a given normalized spatial weight matrix $\boldsymbol{W}$, FD presence is assumed to be generated according to:

$$I = \phi_0 + \rho \boldsymbol{W} I + \phi_1 C + \boldsymbol{X}^\top \gamma + \varepsilon \tag{C.1}$$

with $|\rho| < 1$. We restrict this model to be complete in the sense that $(\boldsymbol{\iota} - a\boldsymbol{W})$ is non-singular for all $|a| < 1$ ($\boldsymbol{\iota}$ is the identity matrix of dimension equal to the sample size). Such spatially-explicit modeling can only be conducted in cross-section, thus we restrict the data the the year 2016 ($N = 738$) while similar results are obtained for 2017. This specification considers $\boldsymbol{W} I$ as an additional endogenous variable that also requires to be instrumented. The Section 6.7 (p.155) of Kelejian and Piras (2017) presents a method to estimate equation (C.1) using spatially lagged values of exogenous regressors as instruments. Importantly, ϕ_1 no longer represents the total causal effect of compliance on FD presence (LeSage and Pace, 2009). This coefficient only captures the direct effect of compliance in a given postal code on its own probability of FD presence. The total causal effect also includes the indirect effects of compliance mediated by the FD presence on neighboring postal codes through $\rho \boldsymbol{W} I$ in equation (C.1).

We use the `spreg` and `impacts` functions from the R package `sphet` to estimate the coefficients reported in Table C.6, with the two spatial weight matrix $\boldsymbol{W}$ used in the previous subsection (i.e., 10 km buffers and 5th order contiguity). As expected, it shows that FD presence is highly and positively autocorrelated between postal codes with autoregressive terms distributed from .6 to .8 accross specifications. The indirect effects of compliance are almost as important as the direct effects, and total effects reported at the bottom of the tables are very close to the values in the main text.

C.3 Accounting for imperfect monitoring

Finally, we address the possibility of incomplete monitoring of the FD, i.e. that some FD clusters are unobserved in the data. Note first that our variable indicating the FD presence comes from several years of mandatory monitoring (4 years in 2016 data, 5 years in 2017) where FD clusters are specifically sought after. It does not seems impossible that 100% of all FD clusters are monitored at the time of our data, given that 40% of postal codes under MCPs are monitored both in 2016 and in 2017. For that reason, we deem unlikely that a significant share of infected postal codes is unobserved. Under perfect monitoring, I^* is directly observed in the data and our 2SLS estimator converges to the true causal effect.

Consider, on the contrary, that we only observe $I = M \times I^*$ where $M \in \{0, 1\}$ represents the monitoring efforts. This allows for the possibility that we do not observe all cases, that is, $\mathbb{E}(I) \leq \mathbb{E}(I^*)$. Note from Table A.1 that $\mathbb{E}(I) = 85\%$ so that $0.85 < \mathbb{E}(I^*) < 1$. This leaves little room for the error in monitoring, and suggests that the potential bias in the 2SLS estimation is small. The size of the total bias would depend both on monitoring errors and on the correlation between the monitoring variable and the instrument, that is, the value of the vineyards. Replacing the unobserved I^* by the observed I in equation (B.5) and using the exact covariance formula for a product of random variables from Bohrnstedt and Goldberger (1969), the 2SLS estimator becomes:

$$\tilde{\beta}_1^{2SLS} = \frac{\mathbb{C}(I, \hat{\lambda}_1 V)}{\mathbb{V}(\hat{\lambda}_1 V)} \approx \mathbb{E}(M)\hat{\beta}_1^{2SLS} + \mathbb{E}(I^*)\frac{\mathbb{C}(M, V)}{\hat{\lambda}_1 \mathbb{V}(V)}. \tag{C.2}$$

This formula is an approximation neglecting third order terms, but is exact for normally distributed random variables. By definition, $0 \leqslant \mathbb{E}(M)$ and $\mathbb{E}(I^*) \leqslant 1$, so that the only sign uncertainty pertains to $\mathbb{C}(M, V)$. If monitoring efforts are uncorrelated with vineyard prices so that $\mathbb{C}(M, V) = 0$, it follows that $\tilde{\beta}_1^{2SLS} > \hat{\beta}_1^{2SLS}$ since $\mathbb{E}(M) \leqslant 1$. In that case, our 2SLS estimator converges to a lower bound of the true causal effect in magnitude. Otherwise, the sign of the bias depends on the size of the second term. Our data set contains partial monitoring data which allows to evaluate this ratio. Table C.7 reports the OLS coefficient from a regression of monitoring efforts on predicted compliance, in order to recover $\mathbb{C}(M, V)/\hat{\lambda}_1 \mathbb{V}(V)$ of equation (C.2).[5] The coefficients are negative and significant for all the six main lists, and our preferred parameters $N = 15$ and $\tau = 1$ yield an estimate of -0.18. Combining the plausible values $\mathbb{E}(M) = 0.9$ and $\mathbb{E}(I^*) = 0.85$ with our preferred estimate $\tilde{\beta}_1 = -0.45$ yields $\hat{\beta}_1 = -0.33$, which lies within the confidence intervals we consider in the manuscript.

[5]The data set includes the share of surveyed acreage for all regions but Aquitaine, which we use as M. Because a regression excluding the large Bordeaux vineyards would not provide representative results, we consider a proxy for this region where monitoring is equal to one in case of FD presence and zero otherwise. This imputation yields a proxy of M biased towards I, suggesting a downward bias in the regression of M on $\hat{\lambda}_1 V$ so that we estimate a lower bound of the true causal effect in magnitude.

D Dynamic benefit-cost analysis

We assess the robustness of our estimates of the infection costs with a dynamically explicit model (Pavan et al., 2012). We relax two simplifying assumptions made in the main text, namely neglecting (i) the spreading dynamics within postal codes and (ii) the costs of uprooting and replanting infected plants (which add to the production losses). To evaluate whether these simplifications could lead to overestimating the costs of noncompliance, we propose a stylized model of the propagation dynamics inside postal codes. In this extended calculation, we account for the imperfect monitoring and calibrate the replanting costs and the other parameters using reports from professional organizations. We consider that newly infected postal code starts with a plausibly small share of infected crops. Let w be the share of infected crops within a postal code during the year it is first reported as infected. Each year, the monitoring efforts allow to find a share M of all infected crops. These crops are replaced by an equal number of new healthy crops. These healthy crops do not produce grapes for k years. The remaining infected crops then spread by the reproduction factor F. Let s_n and u_n be respectively the share of infected crops and the share of crops replanted in year n:

$$\begin{cases} s_n = F(1-M)s_{n-1} = [F(1-M)]^n w \\ u_n = Ms_n = M[F(1-M)]^n w \end{cases} \tag{D.1}$$

As long as $F(1-M) > 1$, the presence of FD is increasing. The infected share increases until u_n reaches 100%, at which point all vineyards are replanted with healthy crops and then infection stops. This happens after a number of year equal to $T = \lceil -\frac{\log(wM)}{\log(F(1-M))} \rceil$. As in the benchmark evaluation of the main text, we compute the benefits of increasing compliance by 10 percentage points, using our preferred estimate of the causal effect of $\beta_1 = -.45$, a total MCP area of $A = 550,000$ ha, an average annual return $R =$ €1,600/ha, and a discount factor $r = .05$. The total cost of FD presence can be divided into three components. First, all vines are replaced after T years, which triggers a full production loss during the next k years. The resulting forgone returns correspond to the benchmark cost delayed by T years, hence discounted by a factor $1/(1+r)^T$. The second component is the discounted sum of the production losses between the start of the infection and year T. These losses are due to intermediary replanting of detected infected crops and the corresponding years of production loss. The last component is the discounted sum of uprooting and replanting costs, which amount to $A \sum_{i=0}^{T} \frac{1}{(1+r)^i} u_n U$, where U is the unitary cost per ha.

We calibrate this model using a range of plausible values found in reports from professional organizations. In Southern France, infections costs were estimated at the parcel level (Richarme et al., 2020), ignoring imperfect FD monitoring. They report that each infected plant contaminate up to 10 healthy crops in one year. In their simulation, the initial share of infected plant w is 1% and they consider a reproduction factor F of 5 for the first year, and then 2 for the following years. Because clusters may saturate after a rapid expansion, we expect the dynamics at the larger postal code scale to be slower. We thus consider a rather conservative range of values $w \in \{1\%, 0.1\%\}$ and $F \in \{2, 3\}$. We also consider an extremely conservative value of $F = 1.7$ implying that 3 infected crops generate only 2 additional infected crops each year.

At the aggregate postal code level, yearly monitoring of the infected crops is likely imperfect.[6]

[6] The symptoms only appear with a delay, so that not all infected crops can be detected immediately. However, this does not stand in contradiction with our view exposed in Section C.3 that most postal codes containing at least one cluster are observed in the data. Inside an infected postal code however, not all infected plants are detected each year.

In their 2020 report, the regional organization in charge of the monitoring and reporting around Bordeaux reported having prospected 30,117 ha over the total of 216,000 ha in vines, which implies a prospecting share of 13.9%.[7] In Occitanie, a 2020 report mentions that 20% of the vineyards have been surveyed that year.[8] In PACA, the local authorities reported in 2020 that about 10% of all vines had been inspected in the last 3 years.[9] As the share of prospected area is likely greater in infected postal codes than at the regional level, we consider $M \in \{20\%, 25\%, 33\%\}$.

Professional organizations routinely report estimates of installation costs including uprooting and replanting costs.[10] These evaluate uprooting costs at around €1,000/ha, and maintenance costs during the first years at around €10,000/ha. Note that our calculation of the annual returns already includes maintenance costs and regular replanting every 20-50 years. This suggests that the accounting costs in the reports overestimate U. We consider smaller values $U \in \{1, 2, 5\}$ in k€.

Fig. D.1 reports the total cost for each set of parameters, and the corresponding values for each of the three components. The number of years until full replanting ranges from 8 years ($F = 3$ and $w = 1\%$) to 62 years ($F = 1.7$, $w = 0.1\%$, and $M = 33\%$). Only for extremely conservative parameters does the dynamic model yield values under the benchmark calculation in the main text, and even these are still above the corresponding compliance costs. Over more plausible ranges of parameters, the extended cost estimates are larger than the benchmark calculation which suggests that the main text provides a lower bound of the cost of noncompliance.

[7] GDON Bordeaux (2020)
[8] Direction Régionale de l'Alimentation de l'Agriculture et de la Forêt Occitanie (2019)
[9] Chambre d'Agriculture Provence-Alpes-Côte d'Azur (2020)
[10] Chambres d'Agriculture Var Bouches-Du-Rhône (2015); Chambre d'Agriculture d'Aquitaine (2017)

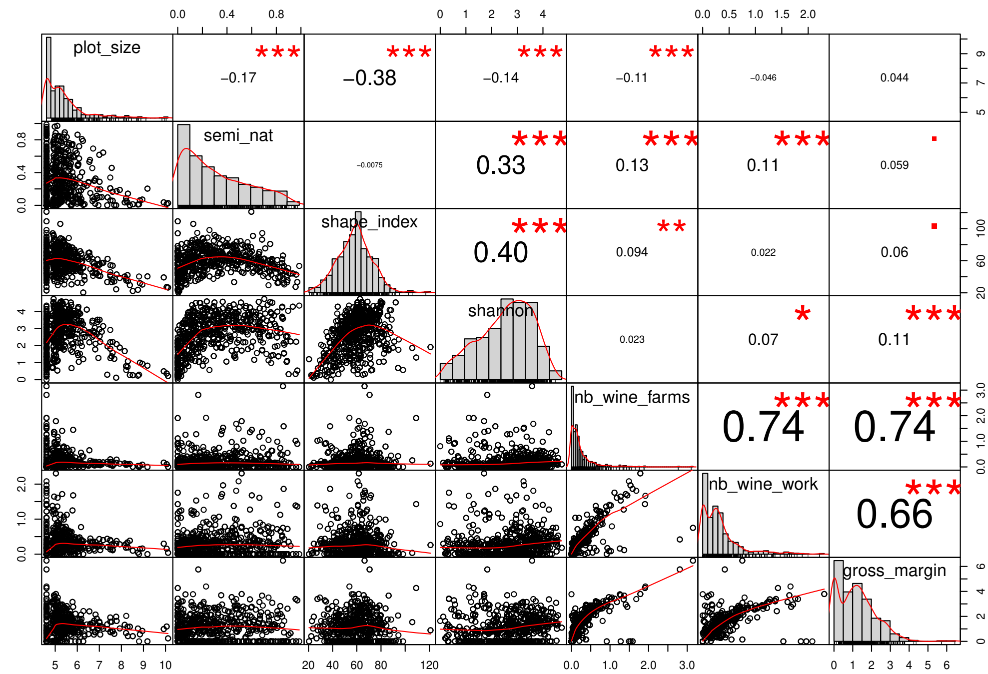
Figures and Tables

Table A.1: Summary statistics of the main variables at the postal code level

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
FD presence	1,586	0.846	0.362	0	1	1	1
FD monitoring	1,586	0.393	0.489	0	0	1	1
Log. 2015 vineyard price	1,586	2.656	0.678	1.609	2.303	2.890	6.795
Log. 1990 vineyard price	1,586	2.433	0.705	0.000	2.121	2.913	5.902
Compliance (N = 10, τ = 1)	1,586	16.740	290.200	0.000	0.392	3.105	11,270.000
Compliance (N = 10, τ = 5)	1,586	38.090	373.000	0.000	0.526	8.500	11,589.000
Compliance (N = 10, τ = 100)	1,586	52.910	543.600	0.000	0.556	9.882	13,244.000
Compliance (N = 15, τ = 1)	1,586	22.800	305.100	0.000	0.502	5.029	11,453.000
Compliance (N = 15, τ = 5)	1,586	47.510	431.300	0.000	0.641	12.530	13,775.000
Compliance (N = 15, τ = 100)	1,586	68.030	726.700	0.000	0.705	13.870	21,058.000
Mean vineyard plot size	1,585	267.500	1,561.000	0.000	0.000	101.500	24,622.000
Percent of semi-natural area	1,585	0.291	0.243	0.000	0.092	0.453	0.986
Landscape shape index	1,585	59.690	14.520	17.890	50.550	69.120	121.000
Shannon diversity index	1,585	2.735	1.056	0.000	2.061	3.533	4.886
Number of wine farms	1,578	129.000	199.800	0.000	0.000	174.000	974.000
Acreage of wine farms	1,578	783.300	1,305.000	0.000	0.000	924.000	7,345.000
Number of wine workers	1,578	232.200	375.500	0.000	0.000	301.500	1,875.000
Gross margin of wine farms	1,578	2,010.000	3,260.000	0.000	0.000	2,464.000	17,617.000
Average temperature	1,586	13.380	1.436	5.207	12.700	14.270	16.120
Cumulative precipitations	1,586	61.360	11.670	38.950	54.090	65.130	112.500
Number of rainy days	1,586	13.040	2.509	7.889	10.960	14.640	20.680
Solar radiation	1,586	83,660.000	2,722.000	73,293.000	81,680.000	86,025.000	90,066.000
Average wind intensity	1,586	2.806	0.817	0.948	2.178	3.356	6.096
Relative humidity	1,586	73.100	4.556	64.560	67.590	76.780	80.630
Number of freezing cold days	1,586	2.819	1.234	0.028	2.164	3.333	10.840
Evapotranspiration	1,586	83.940	12.400	53.100	74.970	93.970	132.100
% of AOCs with Pinot N	1,586	0.007	0.069	0	0	0	1
% of AOCs with Cab. franc	1,586	0.210	0.328	0	0	0.1	1
% of AOCs with Cab. sauv.	1,586	0.195	0.333	0	0	0.03	1
% of AOCs with Chardonnay	1,586	0.021	0.058	0	0	0.03	1
% of AOCs with Gamay	1,586	0.003	0.013	0	0	0	0
% of AOCs with Merlot	1,586	0.240	0.340	0	0	0.1	1
% of AOCs with Sauvignon	1,586	0.259	0.403	0	0	0.8	1
% of AOCs with Grenache	1,586	0.459	0.362	0	0	0.6	1
% of AOCs with Syrah	1,586	0.449	0.361	0	0	0.7	1

Figure A.1: Correlation plots between the additional control variables.

(a) Landscape and agricultural structures



(b) Historical climate variables (1990–2010)

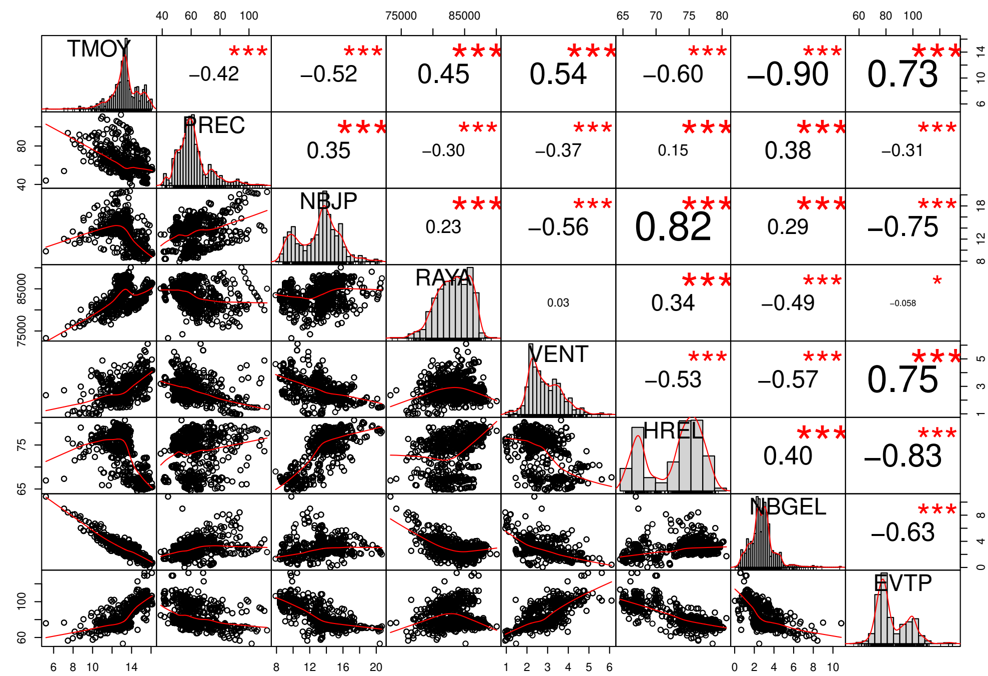


Figure A.2: Regional analysis for the restricted lists of insecticide products.
Notes: The four panels represent the main wine-producing regions of France. The bars show the share of Usable Agricultural Area (UAA, without grasslands) that could be treated with the observed sales of each insecticide product. We distinguish the specialized postal codes and the postal codes without vineyards, to show that products with other uses can be dropped depending on τ. The dotted lines represent the cumulative shares of the most used products over specialized postal codes. The vast majority (>80%) of treatments are applied using the 10 to 15 most used products, depending on the region.

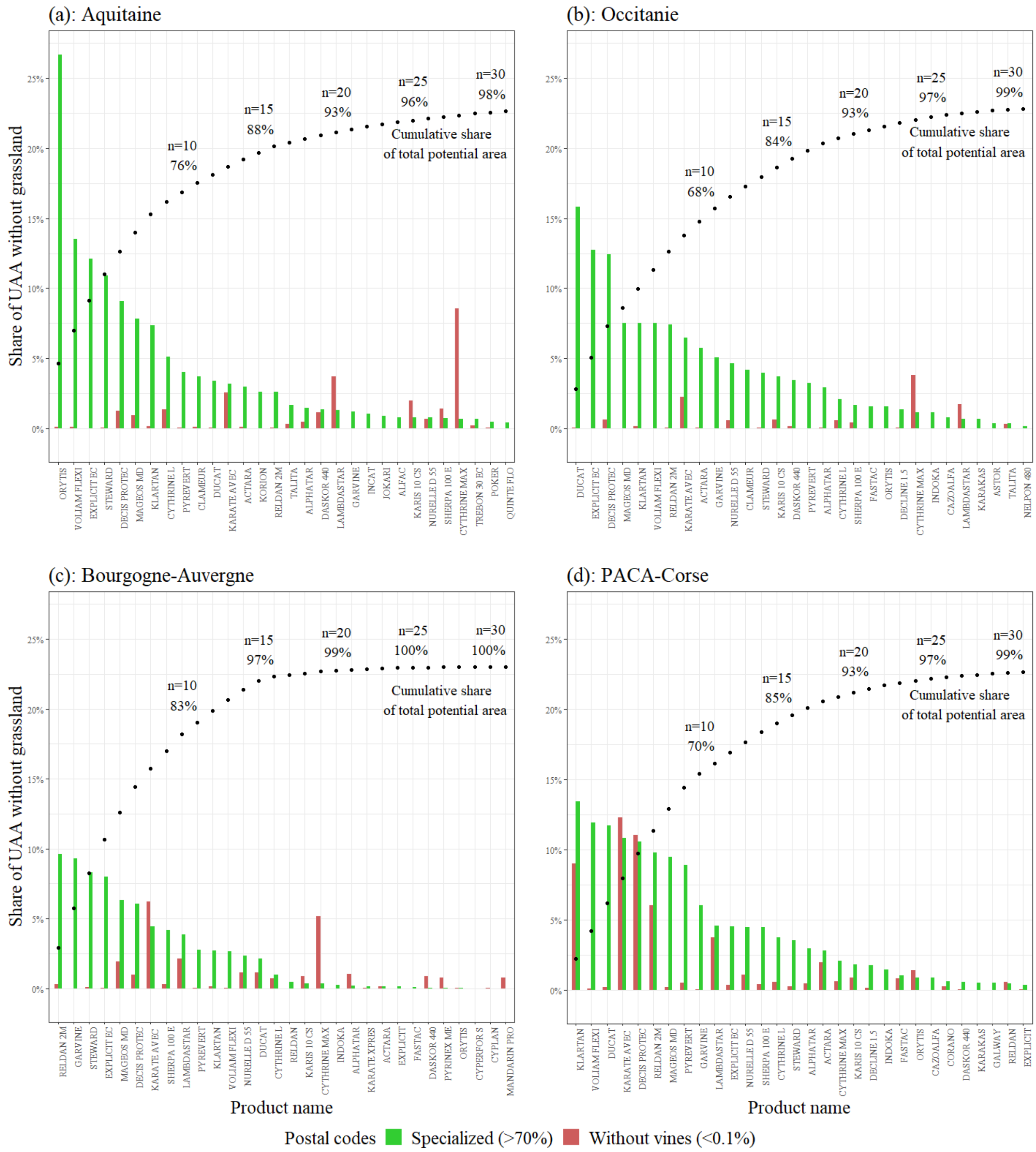


Figure C.1: Specification chart across extended models.

Notes: This plot summarizes the causal effects from the sensitivity analysis. Section C provides the details of each specification presented in the bottom panel of the Figure. The standard errors in parenthesis are HAC from the procedure presented in Kelejian and Piras (2017).

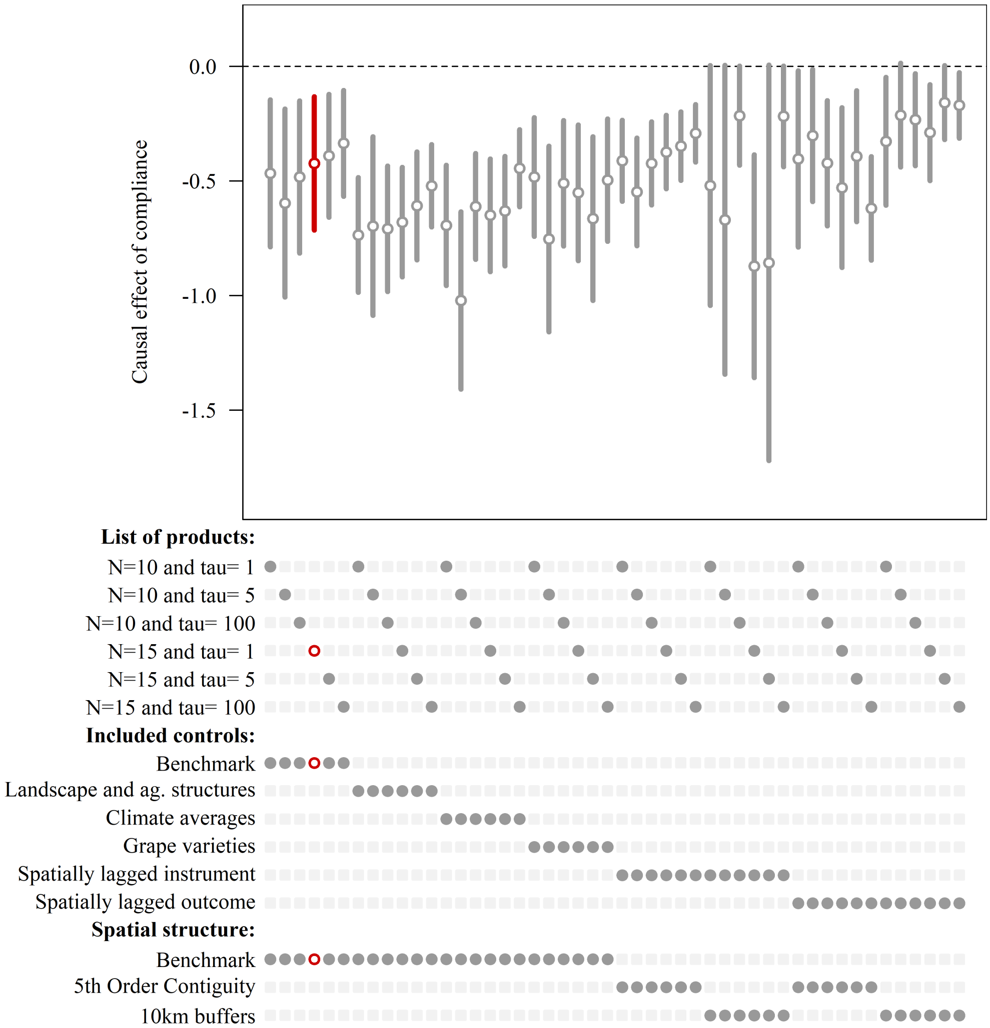


Figure C.2: Partial residual plot for the instrument in the first stage.

Notes: This partial residual plot comes from the regression of compliance rates (with $N = 15$ and $\tau = 5$) on vineyard prices and controls for alternative land uses (rows 5–10 of Table 1 in the main text). The slope of the line is the coefficient λ_1 related to the interaction between acreages to treat and the logarithm of vineyard price deviation in equation B.4 of SI. The averages are weighted by the surface to treat. The points are located in 100 regular bins spanning the interval [-2;4] on the x-axis, with 53 bins containing between 1 and 144 observations. The y-value is above 1.5 for 6 observations and below 0 for 5 observations, so do not appear in the Figure. These points only account for 0.79% of the acreage to treat.

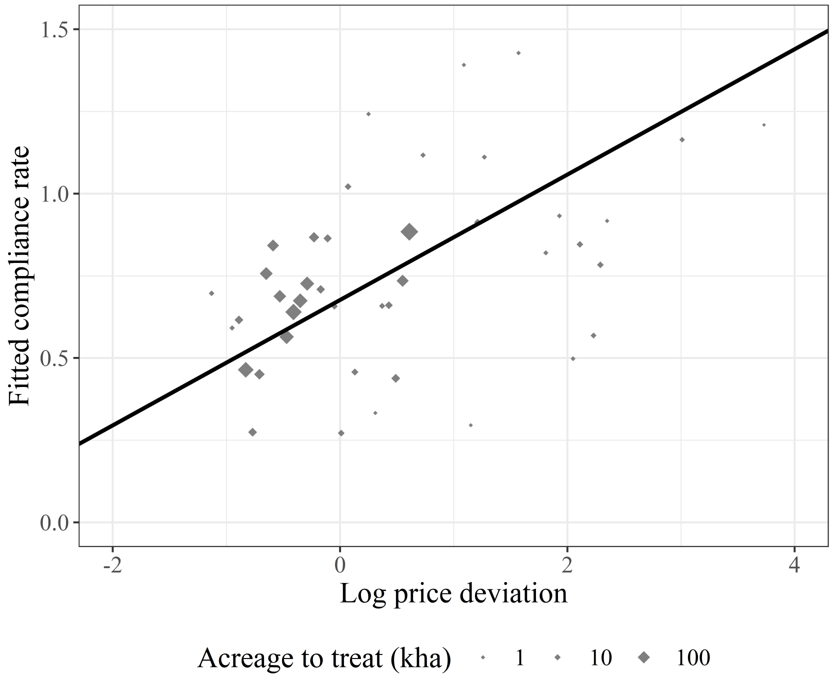


Table C.1: 2SLS results controlling for landscape and agricultural structures

(a) First stage (outcome= acreage actually treated)

	(1)	(2)	(3)	(4)	(5)	(6)
Acreage to treat (ATT)	0.535***	0.662***	0.652***	0.694***	0.777***	0.751***
	(0.040)	(0.048)	(0.049)	(0.047)	(0.054)	(0.054)
Permanent crops	1.128***	1.518***	2.454***	1.501***	2.019***	2.913***
	(0.075)	(0.089)	(0.091)	(0.087)	(0.101)	(0.101)
Annual crops	0.064***	0.130***	0.108***	0.094***	0.187***	0.165***
	(0.008)	(0.009)	(0.010)	(0.009)	(0.011)	(0.011)
Pastures	−0.017*	−0.022*	−0.007	−0.027**	−0.033**	−0.017
	(0.010)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
ATT × log. price deviation	0.101***	0.048***	0.085***	0.103***	0.099***	0.138***
	(0.012)	(0.014)	(0.014)	(0.013)	(0.016)	(0.016)
ATT × Elevation	−0.001***	−0.001***	−0.0004***	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ATT × Mean vineyard plot size	0.00000	−0.00000	−0.00000	−0.00000	−0.00000	−0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
ATT × Percent of semi-natural area	−0.173***	−0.192***	−0.240***	−0.184***	−0.244***	−0.296***
	(0.038)	(0.046)	(0.047)	(0.045)	(0.052)	(0.052)
ATT × Landscape shape index	−0.001	−0.001	−0.0004	−0.002**	−0.002**	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ATT × Shannon diversity index	0.063***	0.059***	0.038***	0.088***	0.091***	0.070***
	(0.012)	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)
ATT × Number of wine farms	−0.0004***	−0.001***	−0.001***	−0.0005***	−0.001***	−0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ATT × Acreage of wine farms	0.0002***	0.0003***	0.0003***	0.0002***	0.0003***	0.0003***
	(0.00003)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Observations	1,577	1,577	1,577	1,577	1,577	1,577
R^2	0.866	0.836	0.844	0.870	0.865	0.874

(b) Second stage (outcome= dummy about FD presence)

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Compliance (N = 10, τ = 1)	−0.736***					
	(0.128)					
Predicted Compliance (N = 10, τ = 5)		−0.697***				
		(0.199)				
Predicted Compliance (N = 10, τ = 100)			−0.709***			
			(0.140)			
Predicted Compliance (N = 15, τ = 1)				−0.680***		
				(0.122)		
Predicted Compliance (N = 15, τ = 5)					−0.608***	
					(0.120)	
Predicted Compliance (N = 15, τ = 100)						−0.521***
						(0.092)
Elevation	−0.0004***	−0.001***	−0.0003***	−0.001***	−0.001***	−0.0003***
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Mean vineyard plot size	0.00001**	0.00001*	0.00001*	0.00001**	0.00001*	0.00001*
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Percent of semi-natural area	−0.155***	−0.177***	−0.202***	−0.154***	−0.181***	−0.182***
	(0.047)	(0.055)	(0.052)	(0.047)	(0.050)	(0.049)
Landscape shape index	−0.0001	−0.001	0.0001	−0.001	−0.001	−0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Shannon diversity index	0.094***	0.091***	0.075***	0.107***	0.103***	0.084***
	(0.013)	(0.016)	(0.012)	(0.015)	(0.015)	(0.012)
Number of wine farms	0.0002***	0.0001	0.0001*	0.0001***	0.0001**	0.0001***
	(0.00005)	(0.0001)	(0.0001)	(0.00005)	(0.00005)	(0.00005)
Acreage of wine farms	1.039***	1.120***	1.112***	1.118***	1.123***	1.037***
	(0.077)	(0.136)	(0.098)	(0.091)	(0.100)	(0.078)
Observations	1,577	1,577	1,577	1,577	1,577	1,577
R^2	0.054	0.042	0.050	0.053	0.050	0.054

Table C.2: 2SLS results controlling for historical climate variables

(a) First stage (outcome= acreage actually treated)

	(1)	(2)	(3)	(4)	(5)	(6)
Acreage to treat (ATT)	0.544***	0.517***	0.516***	0.645***	0.680***	0.695***
	(0.013)	(0.016)	(0.016)	(0.015)	(0.018)	(0.018)
Permanent crops	1.153***	1.579***	2.553***	1.526***	2.061***	2.990***
	(0.076)	(0.092)	(0.093)	(0.090)	(0.105)	(0.104)
Annual crops	0.062***	0.127***	0.106***	0.092***	0.183***	0.163***
	(0.008)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Pastures	−0.019*	−0.023*	−0.007	−0.030**	−0.036**	−0.019
	(0.010)	(0.012)	(0.013)	(0.012)	(0.014)	(0.014)
ATT × log. price deviation	0.105***	0.071***	0.119***	0.112***	0.115***	0.163***
	(0.013)	(0.016)	(0.016)	(0.015)	(0.018)	(0.017)
ATT × Average temperature	−0.081	2.230*	4.276***	−1.104	−1.017	−0.048
	(0.993)	(1.201)	(1.209)	(1.174)	(1.364)	(1.355)
ATT × Squared Average temperature	−4.560***	−7.116***	−8.218***	−4.141***	−5.162***	−4.965***
	(1.091)	(1.320)	(1.329)	(1.291)	(1.500)	(1.489)
ATT × Cumulative precipitations	−3.968***	−4.184***	−3.365***	−5.025***	−5.774***	−4.690***
	(0.659)	(0.797)	(0.803)	(0.780)	(0.906)	(0.900)
ATT × Squared Cumulative precipitations	−1.537***	−1.697**	−1.464**	−1.946***	−2.259***	−2.004**
	(0.595)	(0.719)	(0.724)	(0.703)	(0.817)	(0.812)
Observations	1,586	1,586	1,586	1,586	1,586	1,586
R^2	0.855	0.819	0.833	0.857	0.849	0.862

(b) Second stage (outcome= dummy about FD presence)

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Compliance (N = 10, τ = 1)	−0.693***					
	(0.134)					
Predicted Compliance (N = 10, τ = 5)		−1.021***				
		(0.197)				
Predicted Compliance (N = 10, τ = 100)			−0.611***			
			(0.118)			
Predicted Compliance (N = 15, τ = 1)				−0.649***		
				(0.125)		
Predicted Compliance (N = 15, τ = 5)					−0.631***	
					(0.122)	
Predicted Compliance (N = 15, τ = 100)						−0.445***
						(0.086)
Average temperature	0.193	2.527***	2.863***	−0.467	−0.393	0.228
	(0.395)	(0.609)	(0.659)	(0.411)	(0.407)	(0.395)
Squared Average temperature	−3.562***	−7.668***	−5.423***	−3.090***	−3.660***	−2.609***
	(0.689)	(1.426)	(1.012)	(0.613)	(0.705)	(0.541)
Cumulative precipitations	−2.654***	−4.176***	−1.959***	−3.166***	−3.549***	−1.988***
	(0.576)	(0.816)	(0.487)	(0.652)	(0.712)	(0.491)
Squared Cumulative precipitations	−0.373	−1.041*	−0.203	−0.571	−0.734	−0.199
	(0.455)	(0.543)	(0.436)	(0.479)	(0.500)	(0.435)
Constant	1.192***	1.343***	1.130***	1.234***	1.244***	1.124***
	(0.068)	(0.096)	(0.056)	(0.076)	(0.078)	(0.055)
Observations	1,586	1,586	1,586	1,586	1,586	1,586
R^2	0.024	0.024	0.024	0.024	0.024	0.024

Table C.3: 2SLS results controlling for grape varieties allowed by AOCs

(a) First stage (outcome= acreage actually treated)

	(1)	(2)	(3)	(4)	(5)	(6)
Acreage to treat (ATT)	0.639***	0.612***	0.747***	0.633***	0.702***	0.904***
	(0.046)	(0.055)	(0.056)	(0.055)	(0.063)	(0.063)
Permanent crops	1.053***	1.482***	2.382***	1.465***	1.980***	2.817***
	(0.075)	(0.089)	(0.091)	(0.090)	(0.103)	(0.103)
Annual crops	0.069***	0.131***	0.111***	0.094***	0.184***	0.164***
	(0.008)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Pastures	−0.030***	−0.037***	−0.020*	−0.040***	−0.050***	−0.033**
	(0.010)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)
ATT × log. price deviation	0.106***	0.068***	0.100***	0.093***	0.077***	0.103***
	(0.015)	(0.018)	(0.019)	(0.018)	(0.021)	(0.021)
ATT × % of AOCs with Pinot N	−1.439***	−1.817***	−2.037***	−2.070***	−2.082***	−1.993***
	(0.385)	(0.459)	(0.469)	(0.464)	(0.531)	(0.530)
ATT × % of AOCs with Cab. franc	0.488**	1.086***	1.080***	0.214	0.456*	0.397
	(0.194)	(0.231)	(0.236)	(0.234)	(0.267)	(0.267)
ATT × % of AOCs with Cab. sauv.	0.006	−0.412	−0.238	−0.109	−0.141	0.158
	(0.231)	(0.276)	(0.282)	(0.279)	(0.319)	(0.319)
ATT × % of AOCs with Chardonnay	2.923***	3.607***	2.374***	3.673***	4.444***	3.238***
	(0.500)	(0.596)	(0.609)	(0.602)	(0.689)	(0.689)
ATT × % of AOCs with Gamay	−11.550***	−11.500***	−4.711*	−10.390***	−10.900***	−3.245
	(2.170)	(2.589)	(2.645)	(2.616)	(2.993)	(2.990)
ATT × % of AOCs with Merlot	0.111	0.172	−0.062	0.237**	0.178	−0.134
	(0.091)	(0.109)	(0.111)	(0.110)	(0.126)	(0.126)
ATT × % of AOCs with Sauvignon	−0.436***	−0.582***	−0.670***	−0.096	−0.197	−0.348***
	(0.090)	(0.107)	(0.109)	(0.108)	(0.124)	(0.124)
ATT × % of AOCs with Grenache	−0.523***	−0.812***	−0.773***	−0.268*	−0.503***	−0.525***
	(0.122)	(0.146)	(0.149)	(0.147)	(0.169)	(0.168)
ATT × % of AOCs with Syrah	0.383***	0.687***	0.531***	0.213*	0.387***	0.221
	(0.103)	(0.123)	(0.126)	(0.125)	(0.143)	(0.143)
Observations	1,586	1,586	1,586	1,586	1,586	1,586
R^2	0.869	0.841	0.849	0.866	0.863	0.873

(b) Second stage (outcome= dummy about FD presence)

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Compliance (N = 10, τ = 1)	−0.482***					
	(0.132)					
Predicted Compliance (N = 10, τ = 5)		−0.753***				
		(0.207)				
Predicted Compliance (N = 10, τ = 100)			−0.510***			
			(0.140)			
Predicted Compliance (N = 15, τ = 1)				−0.551***		
				(0.151)		
Predicted Compliance (N = 15, τ = 5)					−0.664***	
					(0.182)	
Predicted Compliance (N = 15, τ = 100)						−0.497***
						(0.136)
% of AOCs with Pinot N	−0.676**	−1.351***	−1.021***	−1.124***	−1.364***	−0.972***
	(0.296)	(0.434)	(0.361)	(0.383)	(0.437)	(0.351)
% of AOCs with Cab. franc	0.546***	1.128***	0.861***	0.429***	0.613***	0.508***
	(0.165)	(0.274)	(0.216)	(0.154)	(0.173)	(0.161)
% of AOCs with Cab. sauv.	−0.108	−0.421***	−0.232	−0.171	−0.204	−0.032
	(0.147)	(0.162)	(0.147)	(0.146)	(0.147)	(0.151)
% of AOCs with Chardonnay	1.415***	2.721***	1.215***	2.031***	2.955***	1.613***
	(0.474)	(0.792)	(0.431)	(0.618)	(0.852)	(0.519)
% of AOCs with Gamay	−12.540***	−15.630***	−9.370***	−12.700***	−14.200***	−8.580***
	(1.638)	(2.405)	(0.999)	(1.676)	(2.044)	(0.902)
% of AOCs with Merlot	0.088	0.164**	0.003	0.165**	0.153**	−0.032
	(0.071)	(0.078)	(0.070)	(0.078)	(0.076)	(0.072)
% of AOCs with Sauvignon	−0.310**	−0.537***	−0.441***	−0.152	−0.230**	−0.272**
	(0.120)	(0.167)	(0.146)	(0.100)	(0.108)	(0.114)
% of AOCs with Grenache	−0.385***	−0.745***	−0.527***	−0.281**	−0.467***	−0.394***
	(0.138)	(0.217)	(0.166)	(0.121)	(0.154)	(0.140)
% of AOCs with Syrah	0.358***	0.691***	0.444***	0.291***	0.430***	0.283***
	(0.114)	(0.184)	(0.129)	(0.104)	(0.127)	(0.103)
Constant	1.111***	1.264***	1.184***	1.152***	1.269***	1.252***
	(0.088)	(0.127)	(0.106)	(0.098)	(0.129)	(0.124)
Observations	1,586	1,586	1,586	1,586	1,586	1,586
R^2	0.091	0.091	0.091	0.091	0.091	0.091

Table C.4: 2SLS results controlling for spatial lag of the instrument (10 km buffer)

(a) First stage (outcome= acreage actually treated)

	(1)	(2)	(3)	(4)	(5)	(6)
Acreage to treat (ATT)	0.133**	0.227***	0.493***	0.036	0.053	0.347***
	(0.056)	(0.068)	(0.069)	(0.065)	(0.076)	(0.076)
Permanent crops	1.117***	1.514***	2.464***	1.503***	2.024***	2.941***
	(0.077)	(0.093)	(0.094)	(0.090)	(0.105)	(0.105)
Annual crops	0.064***	0.131***	0.113***	0.092***	0.186***	0.167***
	(0.008)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Pastures	−0.017	−0.024*	−0.012	−0.026**	−0.033**	−0.019
	(0.010)	(0.013)	(0.013)	(0.012)	(0.014)	(0.014)
ATT × log. price deviation	0.056***	0.044**	0.136***	0.025	0.034	0.134***
	(0.017)	(0.021)	(0.021)	(0.020)	(0.023)	(0.023)
ATT × Lag of log. price deviation	0.178***	0.139***	0.039	0.256***	0.266***	0.156***
	(0.022)	(0.027)	(0.027)	(0.026)	(0.030)	(0.030)
Weak instruments	10.83	4.41	41.99	1.56	2.13	32.98
Observations	1,586	1,586	1,586	1,586	1,586	1,586
R^2	0.851	0.812	0.825	0.856	0.846	0.857

(b) Second stage (outcome= dummy about FD presence)

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Compliance (N = 10, τ = 1)	−0.520*					
	(0.267)					
Predicted Compliance (N = 10, τ = 5)		−0.669*				
		(0.344)				
Predicted Compliance (N = 10, τ = 100)			−0.215*			
			(0.111)			
Predicted Compliance (N = 15, τ = 1)				−1.171*		
				(0.602)		
Predicted Compliance (N = 15, τ = 5)					−0.857*	
					(0.440)	
Predicted Compliance (N = 15, τ = 100)						−0.218*
						(0.112)
Lag of log. price deviation	−0.050	−0.049	−0.134***	0.157	0.086	−0.109***
	(0.062)	(0.062)	(0.025)	(0.166)	(0.130)	(0.034)
Constant	1.209***	1.292***	1.246***	1.182***	1.186***	1.216***
	(0.043)	(0.064)	(0.049)	(0.043)	(0.043)	(0.043)
Observations	1,586	1,586	1,586	1,586	1,586	1,586
R^2	0.046	0.046	0.046	0.046	0.046	0.046

Table C.5: 2SLS results controlling for spatial lag of the instrument (5th order contiguity)

(a) First stage (outcome= acreage actually treated)

	(1)	(2)	(3)	(4)	(5)	(6)
Acreage to treat (ATT)	0.556***	0.544***	0.570***	0.654***	0.689***	0.715***
	(0.010)	(0.013)	(0.013)	(0.012)	(0.014)	(0.014)
Permanent crops	1.066***	1.472***	2.451***	1.430***	1.947***	2.896***
	(0.078)	(0.093)	(0.094)	(0.092)	(0.107)	(0.105)
Annual crops	0.075***	0.140***	0.116***	0.108***	0.202***	0.177***
	(0.008)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Pastures	−0.023**	−0.029**	−0.013	−0.035***	−0.042***	−0.024*
	(0.011)	(0.013)	(0.013)	(0.013)	(0.015)	(0.014)
ATT × log. price deviation	0.158***	0.119***	0.153***	0.174***	0.187***	0.222***
	(0.011)	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)
ATT × Lag of log. price deviation	0.015***	0.021***	0.013**	0.017***	0.022***	0.015**
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Weak instruments	205.37	80.63	133.85	178.7	152.69	223.38
Observations	1,586	1,586	1,586	1,586	1,586	1,586
R^2	0.846	0.810	0.826	0.848	0.839	0.855

(b) Second stage (outcome= dummy about FD presence)

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Compliance (N = 10, τ = 1)	−0.412***					
	(0.090)					
Predicted Compliance (N = 10, τ = 5)		−0.547***				
		(0.120)				
Predicted Compliance (N = 10, τ = 100)			−0.423***			
			(0.093)			
Predicted Compliance (N = 15, τ = 1)				−0.374***		
				(0.082)		
Predicted Compliance (N = 15, τ = 5)					−0.348***	
					(0.076)	
Predicted Compliance (N = 15, τ = 100)						−0.292***
						(0.064)
Lag of log. price deviation	−0.012	−0.007	−0.013	−0.012	−0.011	−0.014*
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	1.080***	1.149***	1.092***	1.095***	1.090***	1.060***
	(0.042)	(0.057)	(0.045)	(0.045)	(0.044)	(0.038)
Observations	1,586	1,586	1,586	1,586	1,586	1,586
R^2	0.025	0.025	0.025	0.025	0.025	0.025

Table C.6: GMM results controlling for spatial lag of the outcome

(a) Outcome equation with 10 km buffers

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.36196*	0.27368	0.3993*	0.4066**	0.24671	0.3549*
	(0.19)	(0.176)	(0.233)	(0.187)	(0.161)	(0.204)
Acreage of permanent crops	0.00101	0.00192***	0.0022**	0.00076	0.00209**	0.00234**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Acreage of annual crops	-0.00021***	-0.00019***	-2e-04***	-0.00021***	-0.00019***	-2e-04***
	(0)	(0)	(0)	(0)	(0)	(0)
Acreage of pastures	-1e-05**	-1e-05**	-1e-05**	-1e-05**	-1e-05**	-1e-05**
	(0)	(0)	(0)	(0)	(0)	(0)
Compliance (instrumented)	-0.2104	-0.09261	-0.11982	-0.20208*	-0.16099	-0.08313
	(0.133)	(0.084)	(0.092)	(0.105)	(0.097)	(0.062)
Autoregressive term	0.75565***	0.77767***	0.66778***	0.73052***	0.79382***	0.70322***
	(0.147)	(0.146)	(0.189)	(0.146)	(0.14)	(0.17)
Observations	738	738	738	738	738	738
Direct impacts	-0.21187	-0.09294	-0.12088	-0.20395	-0.16116	-0.08368
Indirect impacts	-0.1179	-0.03456	-0.07859	-0.1366	-0.1198	-0.04518
Total impacts	-0.32976	-0.1275	-0.19946	-0.34055	-0.28096	-0.12887

(b) Outcome equation with 5th order contiguity

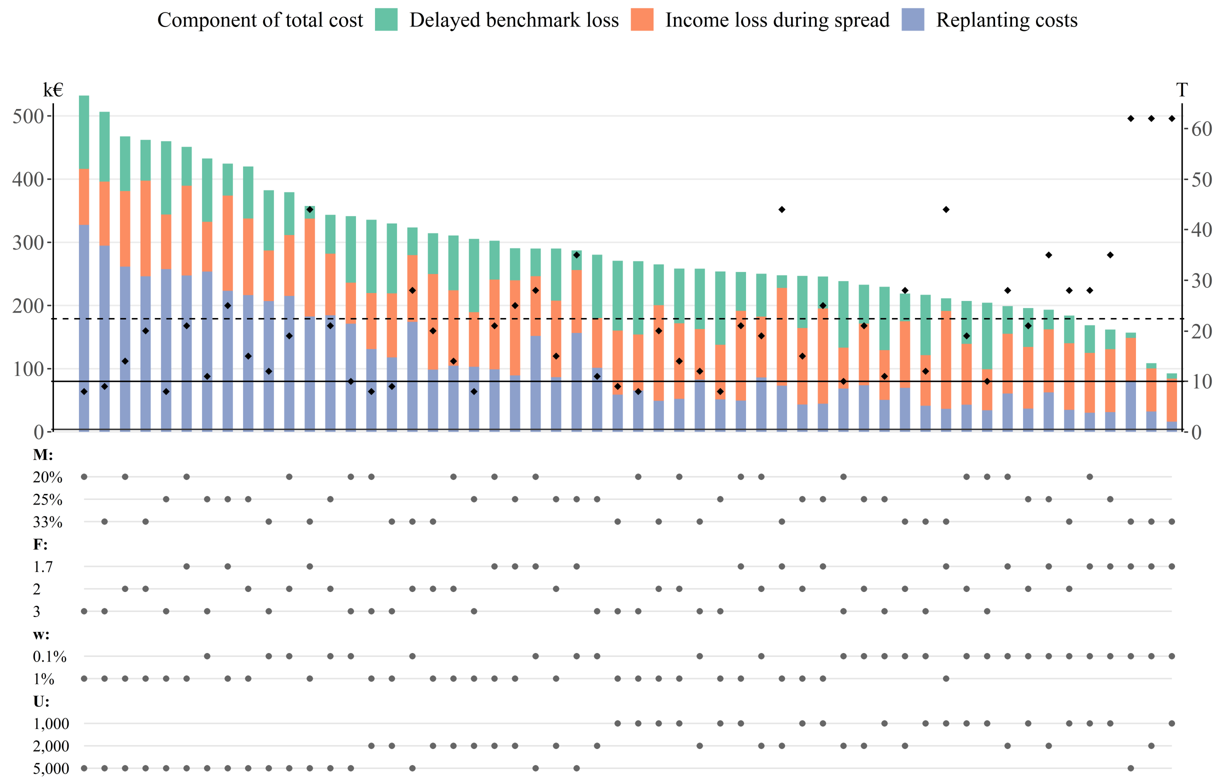
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.48524*	0.47469*	0.5828**	0.49657**	0.43716*	0.53845**
	(0.259)	(0.278)	(0.291)	(0.242)	(0.26)	(0.27)
Acreage of permanent crops	0.00055	0.00206*	0.00227*	0.00015	0.00246*	0.00264*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Acreage of annual crops	-0.00024***	-0.00022***	-0.00023***	-0.00024***	-0.00022***	-0.00023***
	(0)	(0)	(0)	(0)	(0)	(0)
Acreage of pastures	-1e-05**	-1e-05**	-1e-05**	-1e-05**	-1e-05**	-1e-05**
	(0)	(0)	(0)	(0)	(0)	(0)
Compliance (instrumented)	-0.31817**	-0.20749*	-0.22225**	-0.28093***	-0.15482*	-0.1643**
	(0.142)	(0.116)	(0.102)	(0.107)	(0.082)	(0.073)
Autoregressive term	0.69797***	0.65209***	0.55712**	0.7015***	0.68196***	0.5916***
	(0.203)	(0.23)	(0.244)	(0.195)	(0.219)	(0.23)
Observations	738	738	738	738	738	738
Direct impacts	-0.32681	-0.2128	-0.23255	-0.28907	-0.15801	-0.1703
Indirect impacts	-0.29128	-0.18218	-0.30015	-0.26896	-0.11706	-0.18569
Total impacts	-0.61809	-0.39498	-0.5327	-0.55803	-0.27506	-0.35599

Table C.7: OLS regression of monitoring efforts on predicted compliance.
Notes: The reported coefficients are the OLS estimates from regressing the share of monitored vineyard acreages on the predicted values of compliance rates at the postal code level. Monitoring data are not available for the *Bordeaux* region, so we impute them by considering that monitoring is equal to one in case of FD presence and zero otherwise.

	(1)	(2)	(3)	(4)	(5)	(6)
Pred. Compliance (N = 10, τ = 1)	-0.200^{***}					
	(0.064)					
Pred. Compliance (N = 10, τ = 5)		-0.256^{***}				
		(0.082)				
Pred. Compliance (N = 10, τ = 100)			-0.207^{***}			
			(0.066)			
Pred. Compliance (N = 15, τ = 1)				-0.182^{***}		
				(0.058)		
Pred. Compliance (N = 15, τ = 5)					-0.176^{***}	
					(0.056)	
Pred. Compliance (N = 15, τ = 100)						-0.151^{***}
						(0.048)
Constant	1.011^{***}	1.043^{***}	1.017^{***}	1.019^{***}	1.021^{***}	1.005^{***}
	(0.034)	(0.044)	(0.036)	(0.036)	(0.037)	(0.032)
Observations	1,586	1,586	1,586	1,586	1,586	1,586
Note:						*p<0.1; **p<0.05; ***p<0.01

Figure D.1: The cost of noncompliance: benchmark vs. dynamic calculations.

Notes: The value of the benchmark reported in the main text is represented by the horizontal dotted black line. The delayed benchmark loss corresponds to the discounted cost of replanting 100% of the vines after T years. The income loss during the spreading period refers to the discounted sum of production losses before year T. The replanting costs account for the fixed cost of uprooting and replanting each infected crop, which is neglected in the benchmark analysis.



References

Ay, J.-S. and E. Gozlan (2020). Disease dispersion as a spatial interaction: The case of flavescence dorée. *Natural Resource Modeling 33*(3), e12265.

Bohrnstedt, G. W. and A. S. Goldberger (1969). On the exact covariance of products of random variables. *Journal of the American Statistical Association 64*(328), 1439–1442.

Chambre d'Agriculture d'Aquitaine (2017). Coût de plantation d'une vigne palissée.

Chambre d'Agriculture Provence-Alpes-Côte d'Azur (2020). Prospection flavescence dorée, bilan de campagne 2020 en demi teinte. Accessed: 2022-10-01.

Chambres d'Agriculture Var Bouches-Du-Rhône (2015). Référentiel économique du vigneron de la plantation à la mise en marché 2012-2015.

Direction Régionale de l'Alimentation de l'Agriculture et de la Forêt Occitanie (2019). Compte rendu du groupe technique flavescence dorée de la vigne région Occitanie.

Eveillard, S., C. Jollard, F. Labroussaa, D. Khalil, M. Perrin, D. Desqué, D. Desqué, P. Salar, F. Razan, C. Hévin, L. Bordenave, X. Foissac, J. E. Masson, and S. Malembic-Maher (2016). Contrasting susceptibilities to Flavescence dorée in Vitis vinifera, rootstocks and wild Vitis species. *Frontiers in Plant Science 7*, 1762.

Frisvold, G. B. (2019). How low can you go? estimating impacts of reduced pesticide use. *Pest Management Science 75*(5), 1223–1233.

GDON Bordeaux (2020). Bilan flavescence dorée 2020 bassin viticole aquitain.

Kelejian, H. and G. Piras (2017). *Spatial Econometrics*. Academic Press.

Kelejian, H. H. and I. R. Prucha (1998). A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *The Journal of Real Estate Finance and Economics 17*(1), 99–121.

Kelejian, H. H. and I. R. Prucha (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics 157*(1), 53–67.

LeSage, J. and R. K. Pace (2009). *Introduction to Spatial Econometrics*. Chapman and Hall/CRC.

Pavan, F., N. Mori, S. Bressan, and P. Mutton (2012). Control strategies for grapevine phytoplasma diseases: factors influencing the profitability of replacing symptomatic plants. *Phytopathologia Mediterranea 51*(1), 11–22.

Richarme, N., D. Carretier, and P. Palezy (2020). Tout savoir sur la Flavescence Doré.

Tramontini, S., A. Delbianco, and S. Vos (2020). Pest survey card on flavescence dorée phytoplasma and its vector scaphoideus titanus. *EFSA Supporting Publications 17*(8), 1909E.