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"Pesticide Externalities and Spatial Coordination Failure in Mixed Farming Landscapes"

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Pesticide Externalities and Spatial Coordination Failure in Mixed Farming Landscapes*

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Abstract

The coexistence of conventional and low-input farming methods transforms what appears to be an individual optimization problem into a collective action dilemma that subsidies and landscape features alone cannot resolve. This paper provides the first large-scale, field-level causal evidence of how exposure to pesticide externalities from conventional neighbors affects the diffusion of low-input systems through economic channels by creating spatial coordination failures. Using French administrative panel data on 9.5 million agricultural parcels and exploiting quasi-experimental variation in exposure induced by exogenous wind and topographic gradients, I investigate changes in local organic farming adoption and maintenance. Results reveal a modest, but persistent reduction in organic farming of approximately 2.8% relative to the mean, which is above most of exogenous and correlated peer effects. I show that these edge-effect externalities impose heterogeneous costs on organic producers due to certification-threatening risks from involuntary nonpoint source pollution (*via* runoff and drift), and an incomplete insurance market that prevents hedging these shocks. These findings highlight the need for coordinated spatial policies and complementary risk management instruments to mitigate the risk of cross-parcel pesticide contamination.

Keywords: Spatial sorting, Peer effects, Technology adoption, Organic farming, Market failures, Panel data.

JEL Codes: Q15, Q18, D62, D81.

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1 Introduction

Why do greener technologies fail to diffuse, even when subsidized? In agriculture, the European Union (EU) has committed €12 billion to organic farming between 2014 and 2022, and an additional €15 billion through 2027 (European Court of Auditors, 2024) to increase organic farmland from 10% to 25% by 2030 (European Commission, 2021, 2025). However, adoption rates have stagnated despite growing consumer demand and substantial financial incentives. This paper shows how spatial externalities in mixed farming landscapes, where conventional and low-input systems coexist, create coordination failures that hinder the diffusion of technology. This dynamic transforms an individual choice into a collective action dilemma that subsidies and landscape features alone cannot resolve.

Edge-effect externalities (EEEs) from conventional neighbors critically shape the economic viability of low-input systems (Parker and Munroe, 2007; Parker, 2007; Larsen et al., 2024), such as organic farming. Pesticide contamination, in particular, represents a critical yet overlooked barrier. Pesticide drift and runoff, traveling up to 500 meters beyond field edges (Carlsen et al., 2006; de Jong et al., 2008; EFSA, 2014), threaten organic producers with significant economic costs, including de-certification for any detectable synthetic pesticide residues above 0.01 mg/kg (Regulation (EC) 2018/848), forced crop destruction, and legal disputes across Europe and North America (Novak, 2017; Schleiffer and Speiser, 2022; Reboud et al., 2023). Recent years have documented a growing number of incidents. In France, the EU's largest agricultural producer and consumer of pesticides (SDES, 2025), over 200 accidental contamination cases are recorded annually, albeit their broader economic implications remain unexplored.

This paper provides the first large-scale, field-level causal evidence of how exposure to pesticide externalities from conventional neighbors acts as a barrier to the diffusion of organic farming through economic channels. Using French panel data on 9.5 million agricultural parcels from the Land Parcel Identification System (LPIS), I address a central identification challenge: farmers' adoption and location choices are not random. This self-selection, or endogenous spatial sorting, means that naive comparisons between high- and low-exposure areas are fundamentally biased. The empirical strategy is grounded in a random profit model that, by formalizing the economic mechanisms, provides two ways to address endogeneity. First, I include fine-grained individual specific effects to control for unobserved heterogeneity. Second, I exploit quasi-experimental variation from exogenous biophysical factors to address remaining idiosyncratic endogeneity in land use choices. Specifically, historical wind patterns and topography create stable 'shadows'. Parcels located downwind and downslope of conventional ones face systematically higher risk of contamination risk than an otherwise identical parcel located upwind and upslope, *ceteris paribus*. I combine high-resolution wind data from ERA5 reanalysis (Muñoz Sabater, 2019) with digital elevation models (*BD ALTI*®) to construct an exposure index that is, by construction, plausibly orthogonal to farmer characteristics and current land use. I find that pesticide EEEs have a modest but persistent within-parcel effect. A one-standard-deviation (s.d.) increase in exposure reduces the probability of being organic by 0.27 percentage points (pp), or 2.8% relative to the baseline mean.

I demonstrate that these mechanisms arise from the interaction of two market failures. On the one hand, EEEs generate heterogeneous economic costs. By matching LPIS with Farm Accountancy Data Network (FADN) records, I show that biophysical spillovers from conventional neighbors are a double-edged sword for organic farmers: they boost yields *via* free pest control but simultaneously reveal contamination. Critically, these pest control gains remain insufficient to compensate for the yield losses inherent to organic conversion. This asymmetry between both types of producers makes unilateral conversion economically irrational in high-exposure areas. On the other hand, incomplete insurance markets exacerbate this barrier. My analysis reveals that the deterrent effect falls entirely on uninsured farmers and is completely neutralized by insurance. This finding isolates the barrier as financial risk, not an agronomic constraint.

Therefore, this coordination failure fragments the organic sector by driving spatial sorting. The result is a spatial lock-in that traps landscapes in a high-input equilibrium, making them resistant to unilateral policy interventions. Operating at the extensive margin, the effect suppresses entry and accelerates exits in high-exposure areas, thereby precluding the emergence of contiguous organic clusters that internalize externalities. Heterogeneity analysis confirms these economic mechanisms. The deterrent effect of EEEs is twice as strong for high-value perennial crops (e.g., vineyards) facing higher sunk costs. Finally, I use high-resolution remote-sensing data to show that landscape features like hedgerows provide only partial mitigation, leaving the core coordination failure unresolved. These findings call for a policy mix of coordinated spatial planning and complementary risk management instruments to mitigate cross-parcel pesticide contamination.

This paper makes several contributions to the literature. First, I challenge the prevailing focus on positive peer effects in technology adoption in agriculture (see e.g., Foster and Rosenzweig (1995) and Bandiera and Rasul (2006) for knowledge spillovers, BenYishay and Mobarak (2018) and Deperrois and al. (2023) for social learning, and Chabé-Ferret et al. (2024) for social norms). While the literature on organic adoption emphasizes information spillovers and social learning (Parker and Munroe, 2007; Lewis et al., 2011), this paper focuses on the physical constraint of contamination risk. Drawing on the coexistence literature established for GM crops (Beckmann and Wesseler, 2007; Munro, 2008; Desquilbet and Poret, 2014), I model the production choice as a spatial coordination problem. In particular, similar to Missirian (2024) in the case of forced adoption of dicamba-tolerant soybean and cotton varieties in the United States, I study a negative, physically-mediated peer effect: an endogenous externality from neighbors' land use. In addition, my contribution is to disentangle this biophysical mechanism from a comprehensive set of exogenous and correlated peer effects (Manski, 1993), which, to the best of my knowledge, has not been empirically done in this context. I show that EEEs dominate positive peer effects, creating a binding constraint that prevents the development of organic farming. This paper also advances recent work on pesticide EEEs (Larsen et al., 2024; Missirian, 2024) by shifting the focus from whether negative spillovers exist to how they operate. I specifically identify and quantify multiple exposure pathways: pesticide drift, as in Missirian (2024) and Coinon (2022), but also runoff. Indeed, the role of soil persistence (Arias-Estévez et al., 2008) and hydrological transport in pesticide through surface runoff and subsurface flow (Reichenberger et al., 2007), as well as accumulation in downslope positions and drainage pathways (Schulz, 2004), have been identified as the main driver of pesticide externalities. Global meta-analyses demonstrate that runoff and erosion account for up to 4% of applied pesticides leaving agricultural fields, with concentrations in edge-of-field water bodies exceeding regulatory thresholds in 24% of cases worldwide (Stehle and Schulz, 2015). These slope-mediated transport processes dominate pesticide losses particularly during storm events (Lefrancq et al., 2017), when surface runoff can generate pesticide flows 10-100 times higher than baseline flow conditions (Rabiet et al., 2010). Moreover, although recent studies document spillovers, they often fail to address endogeneity and scale effects. My panel, parcel-level approach leverages exogenous geographic variation (wind and topography) to model the anisotropic nature of EEEs. This strategy simultaneously overcomes the two primary identification challenges in the literature on peer effects, i.e., the reflection problem (including endogenous sorting and omitted local factors) (Manski, 1993) and the modifiable areal unit problem (Arbia et al., 1996) that biases aggregate-level studies (see e.g., at the farm level: Läpple and Kelley (2015); at the municipality level: Allaire et al. (2015) and Nguyen-Van et al. (2021); and at the county level: Schmidtner et al. (2011) and Missirian (2024)).[1]

Second, while recent work establishes a link between EEEs and input use (Larsen et al., 2024), the economic mechanisms driving this relationship remain poorly understood. This paper identifies a primary financial mechanism driven by incomplete markets (Sandmo, 1971; Feder et al., 1980; Newbery and Stiglitz, 1981): the risk of uninsurable certification. I argue that this risk poses a significant challenge to sustainable agricultural transitions by reframing the constraints on long-term viability as financial, not merely

[1] Coinon (2022) examines the role of networks in organic farming in metropolitan France across varying spatial specifications, from regional (spillovers) to parcel levels (peer effects). Using an Explanatory Spatial Data Analysis (ESDA) framework (Anselin, 1995, 1996), the magnitude of spatial dependency is confirmed to be highly sensitive to the level of aggregation. Moreover, relying on the French Agricultural Census that records location solely at the headquarters of each farm, the author shows that parcel-level data mitigate measurement error found in farm-level studies. In a matched sample between LPIS and the Agricultural Census for the year 2018, covering approximately 60% of LPIS parcels, 33% are located in a municipality distinct from the headquarters. The granularity of this study is then critical from a spatial econometrics perspective to avoid misspecification of the weight matrix, while also ensuring that the analysis accounts for the relevant unit where these EEEs operate.

agronomic. This distinction is crucial, as the literature on risk management has largely focused on moral hazard, where reactive tools (insurance) are seen as substitutes that crowd out proactive effort (Annan and Schlenker, 2015; Miao, 2020). However, empirical support for this substitution channel is weak (see e.g., Enjolras and Aubert (2020) on pesticide use in France). This paper instead tests an alternative hypothesis grounded in a selection mechanism. Since organic farming entails greater profit volatility, only agents with sufficient financial resilience (proxied here by crop insurance) can afford to bear this increased variance (Rosenzweig and Binswanger, 1993). The decision to adopt is therefore constrained by the farmer's capacity to buffer shocks, as predicted by Just and Pope (1978). This interpretation echoes findings that financial instruments are essential for overcoming household risk-management barriers (Cole et al., 2013) and pivotal in shaping agronomic risk-taking behavior (Mobarak and Rosenzweig, 2013). Consistent with this selection channel, the empirical results demonstrate that insured farmers are significantly more likely to grow organically in mixed farming landscapes.

Finally, I bridge ecological and economic analysis by quantifying a crucial, yet often-overlooked, ecosystem service - the EEE mitigation capacity of landscape infrastructure (Baudry et al., 2000). This paper moves beyond the traditional valuation of hedgerows (e.g., as windbreaks, Ucar and Hall (2001)) to provide the first economic valuation of their critical role in serving as a biophysical barrier against pesticide contamination and enabling coexistence in mixed farming landscapes. My findings show that while *ex-ante* planted hedgerows do help internalize the externality – providing partial, economically meaningful mitigation – they fail to fully resolve the underlying coordination failure.

The remainder of the paper proceeds as follows. Section 2 reviews the institutional background for organic farming and its coexistence with conventional agriculture. Section 3 develops the theoretical model and its key assumptions. Section 4 describes the data and presents the identification strategy. Section 5 reports the main empirical findings and investigates heterogeneity, while Section 6 examines how these effects operate. In Section 7, I analyze strategies to manage coexistence, focusing on landscape features and economic resilience. Finally, Section 8 concludes.

2 Institutional Background

The growing development of organic farming, driven by successive Common Agricultural Policy (CAP) reforms (Sanders et al., 2008; Allaire et al., 2015) and the EU's 2030 target of 25% organic land (European Commission, 2020), has increased the physical interface between conventional and organic parcels. Organic farming represented 16.9 million hectares, or 10.5% of UAA, in the EU in 2022 (European Commission, 2025). This growth creates an economic and ecological challenge: managing pesticide drift and runoff to maintain organic certification integrity, and thereby securing both price premiums and the provision of associated public goods (such as improved water and soil quality, increased biodiversity, and other ecosystemic services; see e.g., Chabé-Ferret et al. (2021)).

Pesticide Residue Contamination and Organic Standards. The core of organic certification is the prevention of chemical contamination. The EU grants organic certification based on strict compliance rules with organic standards that exclude synthetic fertilizers and pesticides, and genetically modified organisms (GMOs), while requiring ecological practices such as crop rotation, mechanical tillage, and (*ex-post*) establishment of hedgerows (Regulation (EC) 2018/848; Regulation (EC) 2021/1165). Still, some naturally-derived substances like copper and spinosad remain authorized (Regulation (EC) 2018/848). Specifically, these EU regulations mandate that pesticide residues in organic products remain below 0.01 mg/kg – a near-zero technical threshold Regulation (EC) 2018/848). This standard creates a unique economic vulnerability and contrasts with other coexistence ones. For comparison, the tolerance for the accidental presence of GMOs in organic products is 0.9% (Regulation (EC) 2018/848, Annex I), a requirement 90 times less stringent.[2] These standards are enforced strictly, and certification bodies must test at least 5% of organic operators annually (Regulation (EC) 2018/848, art. 34(3)). Exceeding the residue limit may result in immediate de-certification, restarting

[2]This threshold is 100 times stricter than for conventional produce. For conventional products, the EU sets Maximum Residue Limits (MRLs) specific to each pesticide-crop combination, typically ranging from 0.01 to 10 mg/kg. For example, the MRL for glyphosate in wheat is 10 mg/kg (Regulation (EC) 293/2013 Annex II, Annex IIIB), for chlorpyrifos in apples is 0.01 mg/kg (Regulation (EC) 2020/1085 Annex V), while for spinosad in tomatoes is 0.7 mg/kg (Regulation (EC) 2022/1406 Annex II). See Regulation (EC) 396/2005.

the multi-year transition period, and loss of price premiums.

This institutional setup transforms pesticide externalities from a technical problem into a market failure (Segerson, 1988; Xepapadeas, 2011), which arises from three interconnected factors.

First, pesticide drift and runoff are a classic technological externality. Atomistic spraying decisions impose uncompensated costs on neighbors (Coase, 1960; Griffin and Bromley, 1982). The polluter (conventional farmer) bears minimal direct costs from damages, while the victim (organic farmer) faces prohibitive transaction costs to contract with multiple upwind and upslope neighbors. These transaction costs are compounded by monitoring, detection, and enforcement costs inherent to atmospheric and hydrological transfers. Second, the strict 0.01 mg/kg residue limit creates a discontinuous damage function that violates standard assumptions in the spatial externalities literature. Contamination below this threshold may be agronomically harmless, but exceeding it triggers a discrete and dramatic loss of revenue through de-certification. Because the polluter does not internalize these losses (Schleiffer and Speiser, 2022), pesticide externalities may lead to socially excessive pesticide application rates. The problem mirrors pollen contamination in GM/non-GM coexistence (Beckmann and Wesseler, 2007; Munro, 2008; Gray et al., 2011; Desquilbet and Poret, 2014) but with a tolerance threshold orders of magnitude stricter, making even minimal transfers economically harmful. Third, the inherent characteristics of agricultural production preclude Coasean bargaining solutions (Coase, 1960). The presence of multiple neighbors, stochastic wind patterns, topography gradients, and heterogeneous crop-dependent application timing and methods often makes bilateral negotiation infeasible.

Legal Framework and Limited Liability. Nowhere is the asymmetry between legal liability and practical enforcement more evident than in the French legal framework. While French regulations prohibit spraying when wind exceeds 19 km/h (Beaufort scale 3) to minimize drift risk, farmers remain liable for any damage regardless of regulatory compliance.[3] Yet, this *de jure* strict liability operates as *de facto* limited liability. Proving causation requires expensive residue testing and precise temporal matching between detected chemicals and specific application events. This enforcement failure weakens conventional farmers' incentives to internalize the externality. Consequently, organic producers are often left to bear the entire burden. This means that adoption is conditional on the *ex-ante* presence of financial or ecological mitigation, or it requires costly *ex-post* investment in these strategies (Veron and Chakir, 2025).

3 Theoretical Model

This section models the production system choice as a spatial coordination problem, driven by nonpoint-source externalities (like pesticide EEEs) that incentivize technological clustering.

Consider a landscape of parcels $i \in \mathcal{P}$, $|\mathcal{P}| = N$, observed annually for $t = 1, \ldots, T$. Let $P_t \subseteq \mathcal{P}$ denote the set of parcels present in year t.[4] A farmer chooses a production system k for each parcel, either conventional (C) or organic (O). Let $D_i^P = 1$ if parcel i uses conventional methods and $D_i^P = 0$ if organic. The profit from parcel i under system k is

$$\pi_{ik} = P_k Y_{ik} - c_{ik} - L_{ik}$$

where Y_{ik} is the expected yield, P_k the price, c_{ik} production costs, and L_{ik} contamination-related losses. I assume that conventional farmers face no such losses ($L_{iC} = 0$). For organic parcels, $L_{iO} = \kappa_i \ell$, where the parameter $\kappa_i \in \{0, 1\}$ is an indicator for a contamination event, with pesticide residues exceeding the 0.01 mg/kg threshold. The penalty $\ell = (P_O - P_C)Y_{iO} + T_{iO} + R_{iO}$ captures the sum of the foregone organic premium, the cost of restarting the transition period (T_{iO}), and reputational losses (R_{iO}).

[3] See the French Order of the 12th September 2006 on the placing on the market and use of plant protection products

[4] While the empirical model (Section 4.2) exploits a panel dimension, the theoretical model focuses on the static trade-offs. I then omit the time index t for notational simplicity.

3.1 Defining Pesticide EEEs

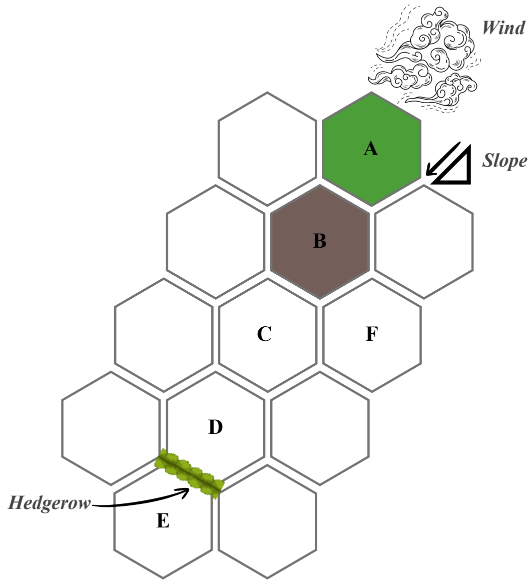
I construct an anisotropic exposure index, θ_i, to quantify the risk of contamination, defined as the aggregate off-target pesticide movement from all non-organic neighbors to the focal parcel i. The index is defined as

$$\forall\, i \in P_t : \quad \theta_i = \sum_{\substack{j \in P_{t-1} \cap B_k(i) \\ j \neq i}} \mathbf{\Theta}_{ij} \tag{1}$$

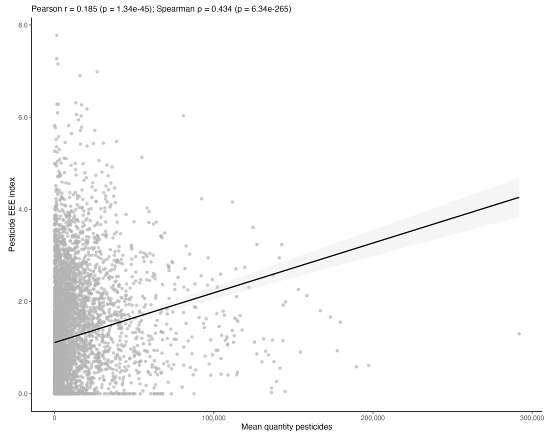
$$\text{where} \qquad \underset{\substack{i \in P_t,\ j \in P_{t-1} \\ j \in B_k(i)}}{\mathbf{\Theta}_{ij}} = w_{ij} a_j D_{jt-1} d_{ij}^{-\delta} \qquad \text{and} \qquad w_{ij} = D_{ij}^W D_{ij}^S \Gamma_{ij}$$

The term D_j^P corresponds to the neighbor's lagged conventional status, ensuring the exposure measure is predetermined with respect to parcel i's contemporaneous choice in year t. The term a_j is the area of any neighboring parcel j, as a proxy for the pesticide in absence of parcel-level data on treatment intensity. The weight $w_{ij} \in [0, 1]$ captures the physical transport pathways. Similar to Deryugina et al. (2019), and later Missirian (2024) and Coinon (2022) for pesticides, I exploit wind direction to identify the causal path of air pollution. The binary variable, D_{ij}^W, denotes whether parcel j is predominantly upwind relative to i during its crop-specific application window based on a five-year historical average of wind patterns. The remaining components, D_{ij}^S and Γ_{ij}, jointly model downslope runoff based on fixed topography. In particular, D_{ij}^S indicates if j is upslope from i and Γ_{ij} proxies the magnitude of the gravitational force along the slope. Exposure decays with distance d_{ij} by parameter $\delta > 0$.

Figure 1a depicts the spatial configuration of six agricultural parcels {A-F}. By assumption, Parcel A (green), managed organically, generates no risk of contamination. Conversely, parcel B (brown) is managed conventionally and is a source of pesticide EEEs. The terrain is characterized by a unidirectional downward slope that originates at parcel A (highest elevation) and terminates at parcel E (lowest elevation). Assuming a prevailing wind from the northeast along the (A,E) diagonal, parcels C, D, and E are situated directly downwind of both A and B. This spatial configuration imposes specific constraints on the contamination matrix ($\mathbf{\Theta}_{ij}$). Given the wind direction, parcel B can-



(a) Landscape network structure



(b) Validity of the index

Figure 1: Construction and validity of the pesticide EEE index in France, 2019-2022

not contaminate its upwind parcel A. Parcel F is located outside this defined aeolian and runoff corridor. Therefore, the set of parcels potentially contaminated by B is, by construction, limited to parcels C, D, and E.

Appendix A details the construction of the neighborhood matrix, $\mathbf{\Theta}_{ij}$, and the rationale behind this index. Consistent with the literature on nonpoint source pollution (Carlsen et al., 2006; de Jong et al., 2008; EFSA, 2014) and the focus on EEEs, I define the neighborhood of parcel i, $B_k(i)$, using a 500m radius (k). The spatial weighting within this neighborhood follows an exponential distance-decay kernel, for which calibration results indicate an optimal decay parameter of 0.005. The validity of this index in capturing pesticide intensity is confirmed by correlating with active substance quantities at the zipcode level from the French national sales database (*Banque Nationale des Ventes des Distributeurs*, BNV-d) for the 2019-2022 period (Figure 1b). As expected, the index exhibits a highly significant positive correlation with the mean annual quantity of active substances applied.

3.2 A Model of Production System Choice

A farmer chooses organic ($D_i^P = 0$) if its expected profit exceeds that of conventional farming, $\mathbb{E}\Big[\pi_{iO}\Big] \geq \pi_{iC}$. Given that conventional farming yields a certain profit π_{iC} and organic farming faces a contamination risk with penalty, this condition can be written as

$$(P_O Y_{iO} - c_{iO}) - \mathbb{E}\Big[L_{iO}\Big] \geq P_C Y_{iC} - c_{iC}$$

Let $\Delta\pi_{iO} \equiv (P_O Y_{iO} - P_C Y_{iC}) - (c_{iO} - c_{iC})$ be the net profit advantage of organic farming, absent any contamination. The expected loss for an organic farm, $\mathbb{E}\Big[L_{iO}\Big]$, depends on the probability of a contamination event. I assume this probability is linear in exposure, such that $\Pr(\kappa_i = 1 \mid \theta_i) = \beta\theta_i$, where $\beta > 0$. The expected loss is therefore $\mathbb{E}[L_{iO}] = \ell \cdot \Pr(\kappa_i = 1 \mid \theta_i) = \ell\beta\theta_i$.

I model the farmer's decision using both a deterministic threshold and a probabilistic choice framework.

A Probabilistic Choice Model.

To account for observed heterogeneity, where farms with similar exposure make different choices, I introduce a farm-specific stochastic term ν_i that represents unobserved costs (e.g., $c_{iO} = c_O - \nu_i$) or non-monetary preferences for organic farming (e.g., environmental preferences (Bonneton, 2025), reputation concerns). The condition for choosing organic becomes

$$\Delta\pi_{iO} - \ell\beta\theta_i + \nu_i \geq 0$$

Assuming ν_i follows a cumulative distribution function (CDF) F, the probability of being organic is

$$\Pr(D_i^P = 0 \mid \theta_i) = \Pr(\nu_i \geq \ell\beta\theta_i - \Delta\pi_{iO}) = 1 - F(\ell\beta\theta_i - \Delta\pi_{iO}) \tag{2}$$

This model predicts a probabilistic relationship where the likelihood of a parcel to be managed under organic farming decreases smoothly in exposure θ_i.

A Deterministic Threshold Model.

As a benchmark, I also test the above predictions under the assumption of homogeneous farmers (i.e., $\nu_i = 0\ \forall i$), in which choices are governed by a simple threshold. A farmer chooses organic if

$$\Delta\pi_{iO} \geq \ell\beta\theta_i \quad \iff \quad \theta_i \leq \frac{\Delta\pi_{iO}}{\ell\beta} \equiv \theta^* \tag{3}$$

All farms with exposure below a critical threshold θ^* choose organic, implying spatial segregation based on exogenous exposure.

3.3 Testable Predictions

This model implies two testable hypotheses regarding the choice of a production system in mixed farming landscapes.

Hypothesis 1 (Deterrence Effect)

A higher level of pesticide EEE exposure reduces the probability that a parcel is farmed organically.

This prediction follows directly from the probabilistic choice model. Differentiating the choice probability in Equation (2) with respect to the exposure index θ_i yields

$$\frac{\partial \Pr(D_i^P = 0 \mid \theta_i)}{\partial \theta_i} = -f(\ell\beta\theta_i - \Delta\pi_{iO})\ell\beta < 0 \tag{4}$$

where $f(\cdot)$ is the probability density function associated with the CDF F. As $f(\cdot)$, ℓ, and β are all non-negative by definition, the derivative is strictly negative. The intuition is that higher exposure raises the expected loss, $\mathbb{E}[L_{iO}]$, for an organic parcel. *Ceteris paribus*, it erodes the profitability of organic production and makes conventional agriculture a relatively more attractive option.

Hypothesis 2 (Spatial Sorting and Strategic Complementarity)

The choice of production system exhibits strategic complementarity, leading to positive spatial autocorrelation and clustering of parcels with similar production systems.

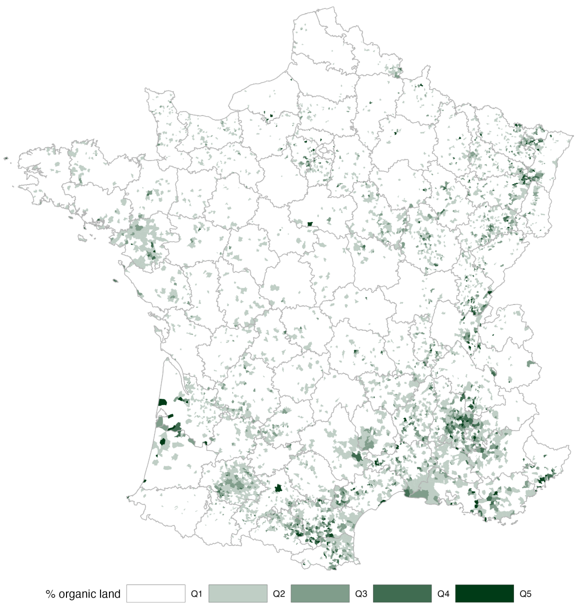
The externality is unidirectional. Conventional farms impose a risk on organic farms, but not *vice versa*. This creates a strategic complementarity in the decision to farm conventionally. Farmer j's choice to be conventional ($D_j^P = 1$) increases neighbor i's exposure index θ_i, which, under Hypothesis 1, reduces i's probability of choosing organic, and thereby increasing their likelihood of choosing conventional.

This interdependence implies that the technology choices of neighboring parcels are positively correlated such that

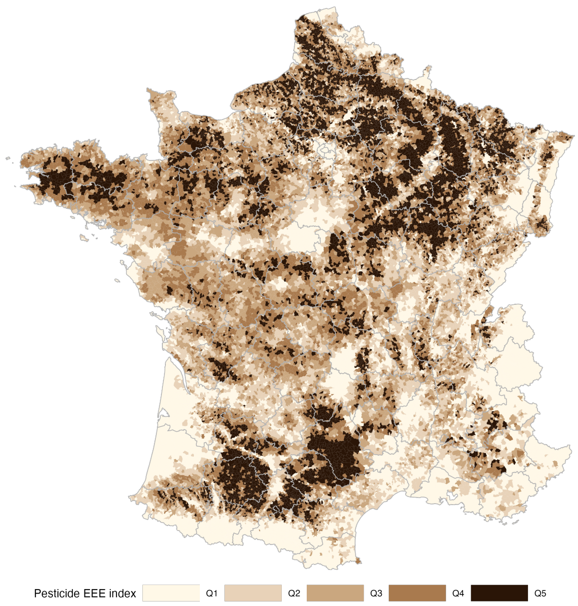
$$\mathrm{Cov}(D_i^P, D_j^P) > 0, \quad \text{and} \quad \frac{\partial\, \mathrm{Cov}(D_i^P, D_j^P)}{\partial w_{ij}} > 0 \tag{5}$$

This mechanism drives a spatial sorting equilibrium. Organic farms have an incentive to locate near other organic farms to minimize their collective exposure, while conventional farms are indifferent to the location of other conventional farms. The aggregate result is the spatial segregation of the two production systems to minimize the costly coexistence between them.

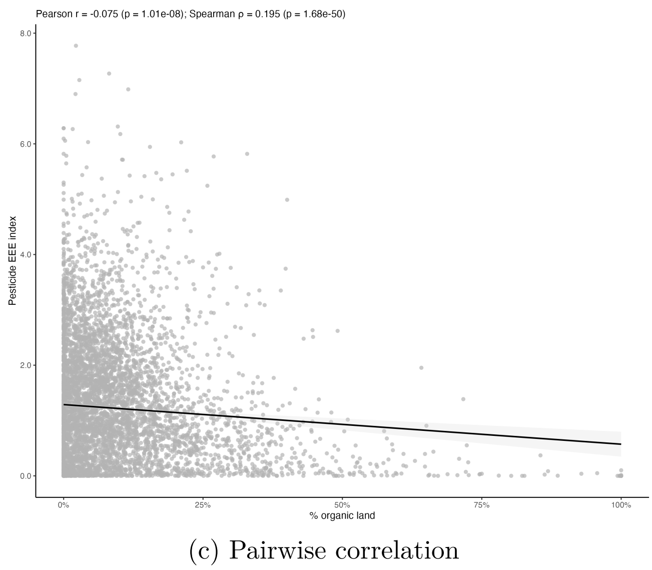
Stylized Facts. Figure 2 provides a preliminary visual support for both hypotheses. Panels 2a and 2b depict the share of agricultural land managed organically and the pesticide EEE index, respectively, at the municipality level. Consistent with Hypothesis 2, Panel 2a shows a clear spatial clustering in organic farming. Organic farming is more prevalent in Alsace and in southern France, particularly in Occitanie, Provence-Alpes-Côte d'Azur (PACA), and the Massif Central. In contrast, the intensive northern plains (Hauts-de-France, Normandy, and Centre-Val de Loire) have rates below 5%. In line with Hypothesis 1, Panel 2b shows that the low-organic areas (northern cereal plains) are precisely those with the highest pesticide EEE index. Moreover, I examine the relationship between the EEE index and the share of organic UAA at the zipcode level (Panel 2c). As expected, these variables are significantly negatively correlated. This confirms that, at an aggregate level, areas with a higher prevalence of organic farming are associated with lower measured risk of contamination.



(a) Share of organic farming



(b) Pesticide EEE index



(c) Pairwise correlation

Figure 2: Organic Farming and pesticide EEE index in France, 2019-2022

3.4 Introducing Risk Management

I extend the model to incorporate two forms of risk management, yielding two additional hypotheses.

Physical Barriers. First, consider physical barriers like hedgerows. Let $h_{ij} \in \{0, 1\}$ be a hedgerow (at the edge) between i and j, and H_i^s a strategically-positioned hedgerow that blocks drift and runoff from a dominant source, defined as $H_i^s = \mathbb{1}\{\exists j \text{ such that } h_{ij} = 1 \text{ and } w_{ij} > \omega\}$, where ω is a threshold defining a dominant pollution direction (e.g., $\omega = 0.5$). For example, in Figure 1a, if there is a hedgerow located exclusively along the boundary between parcels D and E, this barrier shields parcel E from contamination originating from parcel B, but still keeps parcels C and D exposed.

To capture the mitigation effect, I decompose the exposure index conditionally on the presence of a strategic hedgerow:

$$\theta_i = \theta_{i,\text{blocked}} + \theta_{i,\text{unblocked}}$$

where $\theta_{i,\text{blocked}}$ represents contamination from sources up to the first hedgerow encountered (*ex-ante*) along wind and slope vectors, as defined in Equation (1), and $\theta_{i,\text{unblocked}}$ captures residual contamination beyond this barrier.

Hypothesis 3 (Mitigation Effect of Hedgerows)

Strategically-positioned hedgerows mitigate pesticide externalities by physically blocking contamination pathways.

If hedgerows effectively attenuate drift and runoff, exposure originating from beyond the barrier should have a weaker deterrent effect on organic adoption than exposure from unprotected sources. Formally, the marginal effects should satisfy

$$\left| \frac{\partial \Pr(D_i^P = 0)}{\partial \theta_{i,\text{unblocked}}} \right| < \left| \frac{\partial \Pr(D_i^P = 0)}{\partial \theta_{i,\text{blocked}}} \right|$$

Equivalently, in a linear probability specification with both exposure components, this implies $|\beta_{i,\text{unblocked}}| < |\beta_{i,\text{blocked}}|$, where both coefficients are expected to be negative by

Hypothesis 1.

Financial Risk Management. Second, consider financial risk-management instruments. I use crop insurance as a proxy variable. Although this instrument does not *stricto sensu* cover contamination risk, I assume that the purchase decision is non-random and thus, reveals key unobserved farmer characteristics. Farmers who demonstrate rationality and foresight (particularly regarding climate change; see e.g., Deutsch et al. (2018)) are strongly incentivized to purchase crop insurance to manage agronomic risks (Deutsch et al., 2018). This decision then reveals unobserved preferences, such as risk aversion (Binswanger, 1980; Karlan et al., 2014), and, more broadly, signals structural financial resilience (regardless of the source) among insured farmers. Indeed, they have greater financial buffers and a superior capacity to absorb shocks because they maintain financial safety nets.[5] In contrast, the absence of insurance may be indicative of binding liquidity constraints (Rosenzweig and Binswanger, 1993).

I model this as unobserved heterogeneity in risk management, $\xi_i \in \{0, 1\}$, where $\xi_i = 1$ indicates a farmer type with a high propensity to manage risk or greater financial resilience. This heterogeneity implies that the effective loss from contamination, $\mathbb{E}[L_{iO}]$, is perceived differently, because the sensitivity parameter β is a function of this type: $\beta(\xi_i)$, with $\beta(1) < \beta(0)$. The marginal effect of exposure on choice becomes

$$\frac{\partial \Pr(D_i^P = 0)}{\partial \theta_i} = -f\left(\ell\beta(\xi_i)\theta_i - \Delta\pi_{iO}\right)\ell\beta(\xi_i)$$

[5]Note that a model where insurance directly covers contamination losses would be observationally equivalent to the proposed mechanism. In this case, let $\tau_i \in [0, 1]$ be the insurance coverage rate for coexistence losses. Insurance would reduce the effective penalty from contamination, such that the expected loss becomes

$$\mathbb{E}[L_{iO}] = (1 - \tau_i)\ell\beta\theta_i$$

This will directly modify the marginal effect of exposure on the choice of being organic

$$\frac{\partial \Pr(D_i^P = 0)}{\partial \theta_i} = -f\left((1 - \tau_i)\ell\beta\theta_i - \Delta\pi_{iO}\right)(1 - \tau_i)\ell\beta$$

Here, the magnitude of the deterrent effect is mechanically attenuated by the factor $(1-\tau_i)$ and converges to zero as $\tau_i \to 1$. This yields the same qualitative prediction as Equation 6. Given the current institutional framework, standard crop insurance does not encompass these specific certification losses. The empirical findings might reflect unobserved heterogeneity instead of the direct coverage channel that is not present.

Hypothesis 4 (Buffering Effect of Insurance)

A high propensity for risk management moderates the deterrent effect of contamination risk on organic farming. If crop insurance is a valid proxy for this type, the same will be true for insured farmers.

Formally, the above hypothesis means that the marginal effect should satisfy

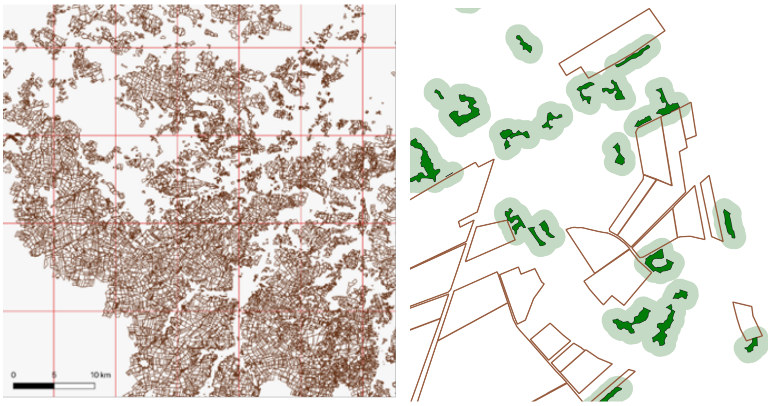
$$\left|\frac{\partial \Pr(D_i^P = 0)}{\partial \theta_i}\right|_{\xi_i=\xi_{\text{high}}} < \left|\frac{\partial \Pr(D_i^P = 0)}{\partial \theta_i}\right|_{\xi_i=0} \tag{6}$$

4 Data and Empirical Strategy

4.1 Data Sources

This paper merges several rich, high-resolution datasets maintained by the Department of Statistics and Foresight Analysis of the French Ministry of Agriculture and Food Sovereignty (Agreste), the National Institute of Geographic and Forest Information (IGN), Agence Bio, and the European Centre for Medium-Range Weather Forecasts (ECMWF). Unique parcel and farmer identification numbers ensure accurate record linkage across these datasets over time. The resulting analysis sample covers 4 years from 2019 to 2022 across nearly 9.5 million parcels, for a total of 38,942,385 observations with data on all main estimation variables. Table 1 presents summary statistics, while Table B1 provides detailed definitions and data sources for all variables used in our analysis.

Land Use and Organic Status. The core of this paper relies on the Land Parcel Identification System (LPIS), an administrative census tracking all agricultural parcels for the management of the CAP. The LPIS provides annual geospatial and agricultural information for over 9.5 million parcels (Figure 3a), including the main crop type, parcel area, and an indicator for organic management. I assume any parcel flagged as organic is fully managed under organic standards across its entire area. I use the national phytosanitary monitoring system (*Bulletins de Santé du Végétal*) to determine crop-specific pesticide application windows. To test the validity of the EEE index for pesticides, I rely on active substance data from the BNV-d database, which is compiled by the annual sales reports transmitted by phytopharmaceutical distributors to the French water agencies.



(a) LPIS parcels (b) Bocage network

Figure 3: LPIS × BDTOPO®: Mapping the landscape structure

Weather and Topographic Data. I use annual weather and detailed topographic data to construct the biophysical exposure measure. First, I use the ERA5-Land reanalysis dataset (Muñoz Sabater, 2019) to extract historical (five-year lagged) monthly gridded wind speed and direction, at $0.1° \times 0.1°$ resolution, during the relevant pesticide application windows. This allows me to model potential pesticide drift and determine the upwind-downwind interaction between a focal parcel and its neighbors. I also extract contemporaneous means of temperature and precipitation to control for agro-climatic conditions. Second, I rely on the *BD ALTI*®, a 25-meter resolution digital elevation model, to model how topography drives surface runoff based on the altitude and slope of the terrain. I identify whether a neighboring parcel is upslope of the focal parcel and incorporate the topographic gradient to proxy the intensity of this flow.

Landscape Features. I also draw on the high-resolution vector dataset *BD TOPO*® to quantify the mitigating role of linear vegetative structures (Figure 3b). I identify hedgerows from the preceding year and treat them as predetermined physical barriers. For each pair of neighboring parcels, I characterize the hedgerows along their adjacent edge and determine their position relative to the defined contamination corridor. I then aggregate this information to the focal parcel level, constructing metrics such as the exposure index separately for areas inside and outside the nearest strategically-positioned hedgerow.

Farm Outcomes and Local Market Context. To test the economic mechanisms, I combine the LPIS with economic records from the Farm Accountancy Data Network (FADN). The FADN provides a representative panel with standardized data on input expenditures (pesticides, fertilizers) and yields. I also report CAP records on crop insurance payments to test the financial risk management channel. Finally, I supplement these records with data from *Agence Bio*, the French public agency for organic agriculture, to capture the local market context, counting the number of organic cooperatives within a 10-kilometer radius to control for local market access.

4.2 Empirical Strategy

To test the theoretical hypotheses (Section 3.3), the objective is causal inference rather than prediction. The causal effect of pesticide EEEs on land use choice is identified using the following two-way fixed effects (TWFE) linear probability model (LPM)

$$\text{Organic}_{it} = \beta\,\theta_{i(t-1)} + \mathbf{X}'_{it}\gamma + \mathbf{Z}'_{it}\zeta + \mathbf{W}'_{it}\rho + \alpha_i + \lambda_t + \varepsilon_{it} \tag{7}$$

where Organic_{it} is an indicator equal to one if the focal parcel i is managed organically in year t, and zero otherwise. The variable of interest, $\theta_{i(t-1)}$, captures an endogenous peer effect (Manski, 1993). This leave-one-out index is constructed from lagged neighboring land use (equivalent to peers' outcome) and weighted by biophysical drift and runoff vectors (Section 3.1). $\mathbf{Z}'_{it}$ corresponds to exogenous (contextual) peer effects through neighbor characteristics. This vector includes variables proxying for 'Marshallian' externalities (i.e., knowledge and information spillovers), such as neighbor UUA with similar crop (following Larsen et al. (2024)) and farmer operational network. The latter variable measures the count of farmers whose operational footprint (the set of municipalities containing their headquarter or parcels) overlaps with that of the focal farmer. The vector

Table 1: Summary statistics of selected variables

Variables	Unit	Mean	St. Dev.	Min	Max
Panel A: Outcome variable					
Organic farming	0/1	0.098	0.298	0	1
Organic conversion (entry) [a]	0/1	0.005	0.073	0	1
Organic deconversion (exit)	0/1	0.002	0.047	0	1
Isolated	0/1	0.525	0.499	0	1
Panel B: Peer effects					
Endogenous peer effects (θ_{it})					
Pesticide EEE index (raw)	-	1.754	2.926	0	874.406
Pesticide EEE index (total, scaled)	s.d. units	0	1	-0.599	298.202
Pesticide EEE index (unblocked, scaled)	s.d. units	0	0.829	-0.320	116.857
Pesticide EEE index (blocked, scaled)	s.d. units	0	0.685	-0.279	298.522
Exogenous peer effects ($\mathbf{Z}'_{it}$)					
Neighbor UUA with similar crop	ha	55.152	62.021	0.000	6,942.640
Farmer operational network	count	44.122	24.085	0.000	577
Total peers in neighborhood	count	46.223	24.651	1	611.000
Correlated peer effects ($\mathbf{W}'_{it}$)					
Tick-market externalities (organic cooperatives)	count				
Importation		0.238	0.787	0	91
Distribution		6.330	9.876	0	1,161
Processing		9.568	12.469	0	1,163
Restaurant		0.047	0.311	0	18
Storage		0.250	0.821	0	67
Transport		0.001	0.031	0	1
Panel C: Additional parcel-level covariates ($\mathbf{X}'_{it}$)					
Parcel size	ha	2.843	7.170	0.010	2,249.490
Own farm UUA	ha	27.170	34.805	0.000	3,907.550
Mean temperature[c]	°C	12.165	1.642	-0.976	16.924
Mean rainfall	mm	0.003	0.001	0.002	0.006
Panel D: Farm-level data ($\mathbf{X}'_{ft}$)					
Yield	s.d. units	-0.005	1.009	-3.481	3.914
Pesticide expenses	€	11,014.907	15,836.642	0.000	305,854.000
Fertilizer expenses	€	13,247.090	17,545.848	0.000	279,941.000
Organic farming	0/1	0.126	0.332	0.000	1.000

Notes: This table presents summary statistics for the 2019-2022 period. Panel D is restricted to the subsample of farms present in the FADN dataset. s.d. units represents standard deviation units. [a] The variable *Organic conversion* equals 1 if a parcel switches from non-organic to organic at time t, and the reverse applies to the variable *Organic deconversion*. These indicators are only computed for parcel–year observations with a valid lag (the first observed year per parcel is excluded), so their mean represents the annual transition share among the eligible parcel–years. The variable *Isolated* is a dummy variable that equals 1 when the parcel has no organic neighbors. [b] Scaled EEE indices are demeaned and divided by the standard deviation of the raw EEE indices, respectively, across 2019-2022. [c] Mean temperature and rainfall are calculated using the previous five years at time t.

$\mathbf{Z}'_{it}$ also includes total peers in neighborhood to measure general agglomeration effects. $\mathbf{W}'_{it}$ accounts for correlated effects that represent shared environmental factors. This vector is primarily composed of variables for tick-market externalities, which measure the density of the local organic supply chain across different actor types (e.g. processing, storage). $\mathbf{X}'_{it}$ is a vector of individual parcel and farm controls, including parcel size, own farm UUA, and crop type fixed effects as well as agronomic suitability controls (mean temperature and rainfall). α_i and λ_t are parcel and year fixed effects, respectively. ε_{it} is the error term.

The identification strategy is designed to isolate the causal effect of pesticide EEEs from two primary challenges: simultaneity in decision-making and endogenous spatial sorting. I overcome these challenges in several ways.

A primary threat to identification is endogenous individual sorting, which would violate the exogeneity assumption through omitted variable bias. This threat arises if farmers self-select into areas based on unobserved, time-invariant characteristics that are correlated with both pesticide exposure and the probability to choose organic farming. For instance, a farmer with a strong, persistent preference for organic methods might be more likely to convert to organic, and intentionally choose a parcel that is intrinsically less exposed to neighbors' pesticides. I control for this unobserved heterogeneity using high-dimensional individual-specific effects (α_i). Then, the coefficient β is identified purely from within-parcel variation, which attributes changes in organic status to changes in a parcel's own lagged exposure.

Another identification assumption relevant to peer effect studies is the reflection problem in decision-making: neighbors' choices influence each other contemporaneously (Manski, 1993). One approach to account for simultaneity is to construct the exposure index $\theta_{i(t-1)}$ using lagged neighboring land use, conditional on its crop-specific pesticide spraying window. By design, a farmer's land use choice in year t cannot retroactively influence their neighbors' choice in year $(t-1)$. This temporal staggering mechanically breaks the simultaneous causality loop.

The identification strategy relies on the standard conditional exogeneity assumption, which is made credible by the granular panel structure of my data. The identifying assumption is that, conditional on parcel-specific effects (α_i), year fixed effects (λ_t), other exogenous and correlated peer effects ($\mathbf{Z}'_{it}$ and $\mathbf{W}'_{it}$, respectively) as well as controls ($\mathbf{X}'_{it}$), the remaining variation in the lagged exposure index $\theta_{i(t-1)}$ is exogenous to unobserved, time-varying determinants of organic farming at time t. The conditional exogeneity assumption is formally stated as

$$\mathbb{E}\left[\varepsilon_{it} \mid \theta_{i(t-1)}, \mathbf{X}'_{it}, \mathbf{Z}'_{it}, \mathbf{W}'_{it}, \alpha_i, \lambda_t\right] = 0$$

The plausibility of this assumption rests on the source of the identifying variation. My identification does not rely on cross-regional comparisons. Instead, it exploits quasi-random, parcel-specific variation in nonpoint source pollution driven by the interaction of lagged neighboring land use with exogenous biophysical factors (namely, prevailing winds and topography), which govern pesticide drift and runoff. Even within the same farm (and thus, conditional on the same farmer and many shared α_i components), two adjacent parcels may experience significantly different pesticide externalities based on their precise positioning. For example, a parcel downwind and downslope of a conventional neighbor will have a systematically higher $\theta_{i(t-1)}$ than an adjacent parcel that is upwind and upslope. This unidirectional, biophysically-driven variation is plausibly orthogonal to unobserved, time-varying determinants of a farmer's choice.

I estimate the model using a LPM. In a panel setting with a high-dimensional set of fixed effects, the linear approximation of the conditional expectation function is a robust approach for causal inference (Angrist and Pischke, 2009; Wooldridge, 2010). It avoids the Incidental Parameters Problem (Neyman and Scott, 1948) that plagues standard non-linear fixed effects estimators. As Greene (2004) shows, unconditional fixed effects estimators for non-linear models are inconsistent as is the number of parcels $N \to \infty$ with fixed T, the number of years. The LPM, by contrast, provides consistent estimates *via* the standard *within* transformation. The coefficient β from the LPM is a direct estimate of the Average Partial Effect (APE) (Angrist and Pischke, 2009), interpreted in percentage points (Wooldridge, 2010).[6]

Given the inherent heteroskedasticity of the LPM (Wooldridge, 2010) and potential serial correlation, I address inference by clustering standard errors at the farm level. The unit of observation is the parcel-year, but the economic decision to adopt organic farming is made at the farm level. This structure implies that unobserved, time-varying shocks (e.g., farm-level financial constraints, shifts in managerial strategy) are shared across all parcels operated by the same farm. Clustering at the farm level allows for arbitrary correlation both within-parcel over time (serial correlation) and, crucially, across-parcels within the same farm at any point in time.

5 Results

5.1 Main Results

Table 2 presents my baseline estimates of the effect of pesticide EEEs on the probability of a parcel being managed organically, using a TWFE LPM with standard errors clustered at the farm level. The main regressor is the standardized exposure index ($\theta_{i(t-1)}$). All specifications include a comprehensive set of agronomic, climate, market, and parcel controls. The columns progressively introduce a more demanding set of spatial fixed effects - from department (Column 2) to commune (3), farm (4), and parcel (5) - along with year fixed effects, allowing me to parse cross-sectional correlations from within-unit responses. Appendix C shows that the results are not sensitive to (i) excluding control variables, (ii) using alternative clustering s.d. and (iii) spatial decays, and (iv) accounting for non-linear effects.

The baseline results provide strong support for Hypothesis 1 (Section 3.3): pesticide

[6] The coefficient of the LPM is a good approximation of the average marginal effect (AME) of the probit or logit, particularly when most probabilities are far from the interval $[0, 1]$, as is the case in this paper. Appendix Figure C1 estimates the model (Equation 7) on cross-sectional samples to ease the computational burden, and confirms that the main findings are robust to Logit and Probit specifications. Alternatives include the Conditional Logit (Chamberlain, 1980), but it operates by discarding all observations that never change state ('non-switchers'). Given 9.5 million parcels, this would likely result in massive data loss. The fixed effects probit is, furthermore, computationally complex and unreliable in this setting.

EEEs pose a significant barrier to organic farming. Across the cross-sectional specifications (Columns 1–3), the coefficient on the endogenous peer effect (i.e., EEE index) is stable and highly significant, ranging from -0.0161 to -0.0175. This implies that a one-standard-deviation increase in exposure decreases the probability of being organic by 1.61 to 1.75 pp, or roughly 16–18% of the 9.8% baseline mean. The coefficient attenuates substantially in the farm fixed-effects model (Column 4), which is expected as this specification absorbs all persistent, farm-level unobserved heterogeneity and spatial sorting. My preferred specification is Column (5). This is the most demanding model as it identifies the effect at the same granular parcel-level at which the biophysical externality itself occurs. This specification exploits strictly within-parcel temporal variation in exposure. It is the most robust to endogeneity concerns as the parcel fixed effect controls for all time-invariant unobserved parcel characteristics and, crucially, all time-invariant farmer characteristics, as the parcel is nested within the farm. The effect remains economically and statistically significant at the 1% level. This within-parcel effect translates to a 2.8% reduction in the likelihood of organic farming, relative to the sample mean, for a one-standard-deviation increase in the EEE index. This persistence provides the strongest causal evidence that pesticide EEEs impede organic farming, beyond any confounding from unobserved spatial or farmer-level heterogeneity.

I also explore the role of other peer effects following the Manski (1993)'s typology. The exogenous peer effects are negligible and sensitive to the fixed-effect structure. A similar negative association was observed between neighbor UUA with similar crop and organic farming. The coefficients for social network proxies (i.e., farmer operational network and total peers in neighborhood) are negligible and reverse signs, indicating that in mixed farming landscapes, the negative biophysical externality prevails over potential positive knowledge spillovers. Moreover, correlated peer effects, proxied by thick-market externalities, show more intuitive results. Local market infrastructure for processing (+0.08 pp in Column 5) and especially storage (+0.21 pp) are the most robustly positive and significant coefficients, suggesting these downstream nodes are supportive of organic transitions. Finally, the individual parcel and climatic controls perform as expected, and all specifications include crop type dummies. Parcel size exhibits a weak positive association in the cross-section which attenuates to zero or becomes negative in the farm and parcel FE models. Mean temperature is negatively associated with organic farming in the preferred parcel FE model, possibly due to greater pest pressure in warmer microclimates. The coefficient suggests that a 1°C increase in temperature is associated with an approximately 16% decline in the likelihood of organic management, relative to the baseline probability. The coefficient on rainfall is very large and negative, but becomes statistically insignificant in all specifications that include spatial fixed effects (Columns 2-5).

5.2 Heterogeneity Analysis

This section investigates the heterogeneity of the main effect, analyzing how it varies by crop type, farm size, and region (Figure 4).

Crop types. The deterrent effect of EEEs is far from uniform across crop types (Panel A), and is strongest for high-value perennial crops consistent with their economic vulnerability. Systems like vineyards require substantial, irreversible investments (for establishment and a three-year organic conversion, Crowder and Reganold, 2015), creating quasi-rents that are highly exposed to contamination. In this case, a single contamination event can jeopardize these multi-year sunk costs, a threat amplified by higher price premiums (Delmas and Grant, 2014) and stricter recertification rules. This explains why the impact is twice as large for vineyards as for annual crops. In contrast, while permanent pastures show a modest but significant deterrent effect, vegetables and flowers appear unaffected.

Farm size. Panel B reveals a clear monotonic relationship between farm size and pesticide EEEs. The magnitude of the deterrent effect is strongest for the smallest farms (Q1) and progressively weakens as farm size increases, though all quartiles are significantly affected. This gradient likely reflects the advantages of scale as larger farms have a greater capacity for risk diversification, lower per-hectare certification costs (Jouzi et al., 2017),

Table 2: Impact of Pesticide Use on the Probability of Being Organic

	Dependent variable: Organic				
			Fixed effects		
	No FE	Dep. + year	Commune +year	Farm + year	Parcel + year
	(1)	(2)	(3)	(4)	(5)
Endogenous peer effects (θ_{it})					
Pesticide EEE index	-0.0175***	-0.0174***	-0.0161***	-0.0005***	-0.0027***
	(0.0003)	(0.0003)	(0.0002)	(0.0000)	(0.0001)
Exogenous peer effects ($\mathbf{Z}'_{it}$)					
Neighbor UUA with similar crop	-0.0001***	-0.0001***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Farmer operational network	0.0003***	-0.0001**	-0.0001**	0.0000**	0.0001***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Total peers in neighborhood	-0.0001***	0.0001**	0.0003***	-0.0000	0.0002***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Correlated peer effects ($\mathbf{W}'_{it}$)					
Tick-market externalities					
Importation	0.0004	-0.0010	-0.0001	-0.0004	-0.0000
	(0.0008)	(0.0008)	(0.0004)	(0.0003)	(0.0003)
Distribution	-0.0004***	-0.0003**	0.0001	-0.0000	0.0001*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Processing	0.0008***	0.0004***	0.0006***	0.0000	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Restaurant	0.0045***	0.0068***	-0.0008	-0.0001	-0.0007*
	(0.0015)	(0.0014)	(0.0006)	(0.0004)	(0.0004)
Storage	0.0055***	0.0011**	0.0027***	0.0023***	0.0021***
	(0.0005)	(0.0005)	(0.0003)	(0.0002)	(0.0002)
Transport	0.0008	0.0094	0.0002	-0.0020	-0.0017
	(0.0085)	(0.0085)	(0.0044)	(0.0020)	(0.0021)
Additional covariates ($\mathbf{X}'_{it}$)					
Parcel size	0.0001***	0.0001***	0.0000	0.0000***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Own farm UUA	0.0001***	0.0001***	-0.0000***	0.0000***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Mean temperature	0.0018***	0.0008	-0.0058**	-0.0015***	-0.0156***
	(0.0005)	(0.0009)	(0.0025)	(0.0004)	(0.0026)
Mean rainfall	-10.8197***	2.3101	7.8770*	-0.8495	-0.6489
	(1.1220)	(2.5447)	(4.4392)	(1.4184)	(2.5639)
Crop type dummies	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	0.0980	0.0980	0.0980	0.0980	0.0980
Main effect (% of mean)	-17.8000	-17.7000	-16.4000	-0.5000	-2.7000
Observations	38,942,385	38,942,385	38,942,385	38,942,385	38,942,385

Notes: Dependent variable is a dummy equal to 1 if parcel i is managed organically in year t. The EEE index is standardized (mean-centered and scaled to unit variance), and results are interpreted as the effect of a one standard deviation increase. Raw exposure values range from 0 to 874.406 with mean 1.755 and standard deviation 2.927. All specifications include the full set of controls for agronomic and climatic conditions, knowledge- and market-based peer effects, and intrinsic parcel characteristics. Standard errors clustered at the farm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

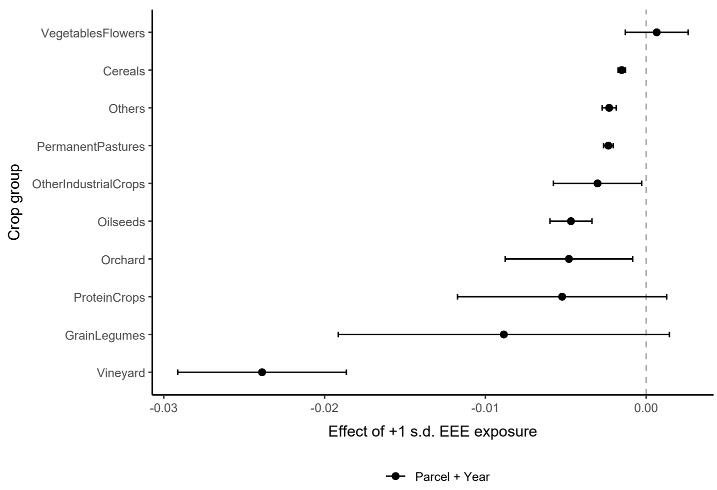
and a superior ability to internalize externalities through internal buffer zones (Parker and Munroe, 2007).

Regional patterns. Panel C highlights significant regional heterogeneity. The effect varies by orders of magnitude across France, mirroring systematic differences in agricultural systems and topography. The majority of French regions show a statistically significant negative effect. The impact is largest in the Mediterranean regions (PACA, Occitanie, Nouvelle-Aquitaine), where a high concentration of vulnerable perennial crops (vineyards, orchards) coincides with complex, steep topography that amplifies runoff. Conversely, in regions where contamination risk is jointly mitigated by flat topography, the dominance of less vulnerable annual crops, and larger consolidated fields, the deterrent effect is statistically insignificant. This is precisely the case in the large cereal-producing plains of Northern France (Hauts-de-France).

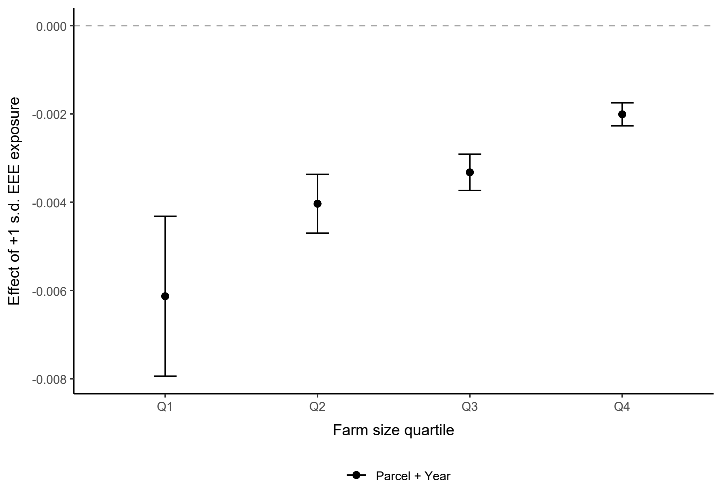
5.3 Impacts of EEEs on Entry and Exit in Organic Production

In Table 3, I also quantify the dynamic impacts of EEEs, examining how exposure drives entry and exit decisions and ultimately shapes the spatial landscape of organic farming.

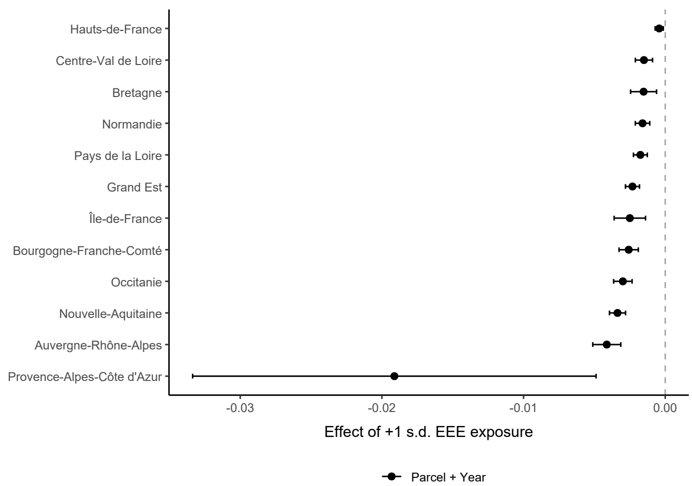
Panel A reveals that pesticide externalities operate primarily as a barrier to entry. A one-standard-deviation increase in exposure reduces the probability of conversion to organic by 6.1% relative to the baseline hazard (Panel A.1, Column 5). In contrast, the effect on exit decisions is less pronounced. The parcel-level exit hazard is modest (2.8% of the mean) and not robust to the inclusion of parcel fixed effects (Panel A.2, Column 5). This suggests that exit decisions are not responses to parcel-specific shocks but are instead driven by farm-level exposure patterns. This asymmetry provides strong evidence for a real options channel (Dixit and Pindyck, 1994; Folta et al., 2006): farmers anticipate the high, irreversible costs of conversion, which manifests as a strong deterrent to entry but a weak effect on exit. Panel A.3 pinpoints the isolating effect of high exposure. Controlling for other peer effects and parcel attributes, high exposure increases the probability of an organic parcel being geographically isolated (i.e, having no immediate neighbors) by



(a) Crop types



(b) Farm size



(c) Regional patterns

Figure 4: Heterogeneity analysis

2.6% of the mean.

Panel B examines farm-level responses, disentangling the extensive margin from the intensive margin. The results demonstrate that EEEs operate primarily at the extensive margin, driving full exits rather than minor adjustments. The hurdle decomposition (Panel B.3) is most revealing, showing the deterrent effect operates almost entirely at the extensive margin. The probability of a farm deconverting any land is highly sensitive to exposure (AME = -6.5 pp, significant at the 1% level), overshadowing any intensive margin adjustments. Indeed, once the exit threshold is crossed, the intensive margin appears irrelevant. Conditional on the decision to exit, the share of land deconverted shows no significant response to EEE levels. This points to a threshold behavior (Chavas and Holt, 1990; Key and Roberts, 2009): farmers opt for complete abandonment over marginal acreage adjustments.

Together, these findings thus underscore the strategic complementarity in production choices - a dynamic driven by unidirectional externalities, as predicted by Hypotheses 1 and 2 (Section 3.3). This asymmetric spatial interaction, where organic farmers benefit from proximity while conventional farmers impose uninternalized costs, actively fragments the organic sector. This externality precludes cluster formation and isolates existing producers.

6 Economic Mechanisms

Section 5 establishes that pesticide externalities can be a significant barrier to organic farming. In this section, I investigate the underlying economic mechanisms. By merging LPIS data with farm-level economic data from FADN, I test the hypothesis that this deterrence is driven by the costs associated with exposure. These costs may be immediate, *via* direct damage to production, or prospective, *via* an (indirect) increased risk of organic de-certification. In this case, I posit that the risk of involuntary exit is realized if the contamination becomes visible at the parcel level, which may happen precisely if the pesticide externalities have a positive production effect (e.g., weed suppression, higher

Table 3: Dynamic Margins of Organic Conversion and Deconversion

	Dependent variable				
	Fixed effects				
	No FE	Dep. + year	Commune +year	Farm + year	Parcel + year
	(1)	(2)	(3)	(4)	(5)
	Panel A: Parcel-level transitions and spatial isolation				
	A1. Adoption hazard				
Pesticide EEE index	-0.0004***	-0.0004***	-0.0004***	0.0001***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Mean dependent variable	0.0090	0.0090	0.0090	0.0090	0.0090
Main effect (% of the mean)	-4.6000	-4.9000	-4.1000	1.6000	-6.1000
Observations	23,207,590	23,207,590	23,207,590	23,207,590	23,207,590
R^2	0.0090	0.0120	0.0440	0.5490	0.7620
	A2. Deconversion hazard				
Pesticide EEE index	0.0007*	0.0008**	0.0006**	0.0000	0.0007
	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0007)
Mean dependent variable	0.0250	0.0250	0.0250	0.0250	0.0250
Main effect (% of the mean)	2.7000	3.1000	2.3000	-0.2000	2.8000
Observations	2,454,918	2,454,918	2,454,918	2,454,918	2,454,918
R^2	0.1130	0.1200	0.2360	0.4790	0.7040
	A3. Isolated status				
Pesticide EEE index	0.0208***	0.0217***	0.0172***	0.0108***	0.0138***
	(0.0004)	(0.0004)	(0.0003)	(0.0002)	(0.0004)
Mean dependent variable	0.5250	0.5250	0.5250	0.5250	0.5250
Main effect (% of the mean)	4.0000	4.1000	3.3000	2.1000	2.6000
Observations	38,942,404	38,942,404	38,942,404	38,942,404	38,942,404
R^2	0.0730	0.1410	0.3950	0.4920	0.9050
	Panel B: Farm-level adjustment margins				
	B1. Deconversion rate (flow)				
Area-weighted pesticide EEE index[a]				-0.1577	
				(0.1218)	
Semi-elasticity %				-14.5900	
QR effect %				-11.1000	
Mean risk-set share				0.7790	
Observations				30,107	
Pseudo-R^2				0.7570	
	B2. Share of UAA under organic management (stock)				
Area-weighted pesticide EEE index				-0.0070 ***	
				(0.0006)	
Mean dependent variable				0.1060	
Observations				1,270,474	
R^2				0.9520	
	B3. Extensive vs. intensive decomposition				
Any deconversion (extensive margin)					
Area-weighted EEE index				-0.2213***	
				(0.0772)	
AME (pp)				-6.5390	
Mean dependent variable				0.1380	
Observations				26,342	
Pseudo-R^2				0.0640	
Conditional magnitude (intensive margin)					
Area-weighted EEE index				-0.2094	
				(0.1320)	
Semi-elasticity %				-18.8900	
AME (pp)				-6.5390	
IQR effect %				-14.5700	
Mean dependent variable (any deconversion)				0.1380	
Observations				14,870	
Pseudo-R^2				0.8910	

Notes: The EEE index θ_i is standardized (mean-centered and scaled to unit variance), and results are interpreted as the effect of a one standard deviation increase. Raw exposure values range from 0 to 874.406 with mean 1.755 and standard deviation 2.927. All specifications in Panel A include the full set of controls for agronomic and climatic conditions, knowledge- and market-based peer effects, and intrinsic parcel characteristics (including crop type). Adoption (i.e., conversion) and deconversion hazards are estimated on the risk set $\{\text{Organic}_{t-1} = 0\}$ and $\{\text{Organic}_{t-1} = 1\}$, respectively, while the isolated status is estimated on the full sample. The main coefficients on θ_i can be interpreted as changes in probability points. At the farm-year level (Panel B), the area-weighted farm-year index ([a]) is

$$\bar{\theta}^A_{ft} = \frac{\sum_{i\in\mathcal{P}_{ft}} A_{it}\,\theta_{it}}{\sum_{i\in\mathcal{P}_{ft}} A_{it}}$$

where $\mathcal{P}_{ft}$ is the set of parcels belonging to farm f observed in year t, A_{it} the area of parcel $i \in \mathcal{P}_{ft}$ and by θ_{it} the raw (non-standardized) parcel-level exposure index. For comparability, I standardize this farm-year index across the estimation sample: $\tilde{\theta}_{wft} = (\bar{\theta}_{wft} - \mu_{\bar{\theta}_w})/\sigma_{\bar{\theta}_w}$. Unless stated otherwise, coefficients in Panel B correspond to a one–standard–deviation increase in $\tilde{\theta}_{wft}$. In Panel B1, I estimate a PPML model of hectares deconverted on $\tilde{\theta}_{wft}$ with a *log offset* equal to the organic area at $t-1$. Coefficients are reported as semi-elasticities, that is a one–s.d. increase in $\tilde{\theta}_{wft}$ changes the deconversion rate by $100 \cdot (\exp(\beta) - 1)\,\%$. In Panel B2, I run an LPM where the dependent variable is the farm-level share of UAA under organic management. Coefficients are in percentage points. Panel B3 corresponds to a hurdle decomposition, the extensive margin (any deconversion) is estimated with a complementary log–log link, where I report average marginal effects in probability points. The conditional intensive margin (magnitude given deconversion) re-estimates PPML on the subsample with positive deconversion, using the same log offset as in the rate specification. Standard errors clustered at the farm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

productivity even when managing under organic), transforming the risk of contamination into a verifiable and tangible event.

Following Chabé-Ferret et al. (2021), I estimate a TWFE panel model that exploits within-farm temporal variation in pesticide EEE exposure while controlling for time-invariant farm-specific characteristics (χ_f) and aggregate time trends (μ_t), such that

$$Y_{ft} \;=\; \psi\,\bar{\theta}_{f(t-1)} + \vartheta\,\text{Organic}_{ft} + \mathbf{X}'_{ft}\eta + \chi_f \;+\; \mu_t \;+\; \epsilon_{ft} \tag{8}$$

where Y_{ft} is an economic outcome for farm f in year t, either normalized yields or input spending (in euros). The variable $\bar{\theta}_{f(t-1)}$ is the farm-level average exposure to pesticide EEEs from neighboring agricultural activities. I control for organic status (Organic_{ft}), a binary indicator equal to one if farm f operates at least one organic parcel in year t. This variable, constructed from LPIS,[7] addresses potential confounding if farms endogenously transition to organic production in response to exposure trends. The vector $\mathbf{X}'_{ft}$ includes the total farm UUA (in hectares) and the type of agricultural products produced by the farm ($OTEX$ classification) in order to capture scale effects and compositional changes in production orientation. Standard errors are clustered at the farm level to account for serial correlation in outcomes and exposure within farms. In supplementary analyses, I also use two-way clustering (farm×year) and spatial clustering (municipality and department) to account for potential correlation across nearby farms. Results are qualitatively robust across all specifications (Appendix C). ψ measures the s.d. change in yields per unit increase in the EEE index, or is expressed in euro change for input spending. The coefficient ϑ identifies the effect of transitioning to organic production, conditional on pesticide EEEs and farm characteristics.

To explore heterogeneity in exposure effects across farming systems, I re-estimate the model separately for conventional and organic farm subsamples, excluding the organic status.

[7] Using LPIS to average the parcel-level status at the farm level allows me to overcome a measurement problem, as the reported organic status in FADN surveys is subject to under-reporting.

6.1 Main Results

Table 4 presents farm-level regressions on productivity, estimated for the full sample and for conventional and organic farms separately. The results highlight the heterogeneity of how pesticide externalities affects yields across different types of farms, and provide an economic rationale for the spatial risk-avoidance behavior documented above.

Column (3) shows that, for organic farms, a one-unit increase in the EEE index is associated with a 0.206 s.d. increase in yields. The positive coefficient of $\bar{\theta}_{f(t-1)}$ is statistically significant at the 5% level, offering direct evidence of the contamination-revelation mechanism. Organic farms may experience involuntary productivity gains in the short run. Consistent with the literature (Chabé-Ferret et al., 2021), I confirm the well-documented yield gap between organic and conventional farms. Yields decrease substantially among organic farmers (0.42±0.21 units of a s.d.), all else being equal. Notably, the impact of pesticide EEEs on organic farms (Column 3) accounts for about half of the gap. This finding suggests that pest control gains from conventional farms substantially narrow the economic performance gap between both producer types, but never compensate it entirely. Additionally, this reliance undermines the integrity of organic certification by revealing a systematic dependence on prohibited neighboring inputs.

Conversely, and as predicted by Hypothesis 2 (Section 3.3), conventional farms derive no significant productivity benefit from external exposure (Columns 1 and 2). In this case, the marginal product of external pesticide exposure is near zero, as their own intensive applications already account for pest management.

6.2 Alternative Mechanisms

This section discusses whether the impact on the economic performance of organic farmers reflects contamination-revelation mechanisms or alternative strategies, such as voluntary intensification or the adoption of complementary practices.

Table 5 supports the hypothesis that these farms use intensive pest control practices. Conventional farms do not see a significant change in pesticide spending after exposure (-42.223±201.83€), while it increases significantly, at the 5% level, by 654.84±613.36€ for

Table 4: Heterogeneous Productivity Effects

	Dependent variable: Yields (normalized)		
	All farms	Conventional	Organic
	(1)	(2)	(3)
Pesticide EEE index	0.030	0.011	0.206**
	(0.026)	(0.027)	(0.091)
Organic	-0.420***		
	(0.104)		
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Farm FE	Yes	Yes	Yes
Observations	20,830	18,443	2,387
R^2	0.480	0.488	0.499

Notes: $\bar{\theta}_{f(t-1)}$ is the mean of the parcel-level EEE index ($\theta_{i(t-1)}$). *Organic* represents farms with at least one parcel certified under organic. All regressions include farm fixed effects and year fixed effects. Standard errors are clustered at the farm level. *p<0.1; **p<0.05; ***p<0.01

organic farms. For organic farms, pesticide spending only comprises approved biological controls (e.g., *Bacillus thuringiensis*, botanical extracts) and mineral treatments (copper, sulfur compounds), which differ fundamentally from the synthetic products applied by conventional neighbors.

Columns (4)-(6) examine fertilizer expenditures as a placebo test. Pest control spillovers should affect pest-related outcomes but not soil nutrient management. Consistent with this prediction, exposure generates no significant effect on fertilizer spending for any farm type.

This pattern is consistent with contamination-revelation operating alongside partial defensive responses. Organic farmers increase their spending on approved pest management tools in response to environments with higher pest pressure, even though they benefit from the involuntary spillover of pest suppression from their neighbors' synthetic treatments. The fact that yields rise despite increased defensive spending suggests that the involuntary spillover effect may dominate. Combined with previous results, I may then rule out general intensification as an explanation for the productivity gains, as well as those on agglomeration economies. Indeed, if productivity gains reflected shared infrastructure or knowledge spillovers, or just complementary practices, we would observe similar effects for conventional farms and effects on non-pest-related outcomes like nitrate management. Furthermore, farms in high-exposure areas may engage in additional management practices that increase yields independently. However, the farm fixed-effects specification eliminates the effects of time-invariant practice differences and identifies effects from within-farm temporal variation in exposure. Another factor that could explain is selection on unobserved quality. In this case, selection would predict higher baseline yields in areas with high exposure. It would require explaining why productive farmers choose locations that Section 5.2 shows they actively avoid (i.e., strong entry deterrence and exit responses).

Table 5: Testing Alternative Mechanisms

	Dependent variable: Input spending (€)					
	Pesticides			Fertilizers		
	All farms	Conventional	Organic	All farms	Conventional	Organic
	(1)	(2)	(3)	(4)	(5)	(6)
Pesticide EEE index	59.235	-42.223	654.843**	-137.963	-342.788	543.087
	(95.727)	(100.914)	(306.681)	(162.960)	(177.829)	(496.800)
Organic	-2,230.619***			-2,453.588***		
	(544.733)			(643.548)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Farm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,444	21,193	3,051	24,444	21,193	3,051
R^2	0.950	0.951	0.946	0.906	0.906	0.893

Notes: Organic represents farms with at least one parcel certified under organic. Pesticide expenditures include all farm spending on plant protection products as reported in FADN accounts, measured in euros. For organic farms (columns 3 and 6), pesticides refer exclusively to products authorized under organic farming regulations (e.g., biopesticides, natural substances such as copper-based fungicides, sulfur, and biological control agents). Fertilizer expenditures refer to nitrogen-based fertilizer spending. $\bar{\theta}_{f(t-1)}$ is the farm-year, average of parcel-level EEE index. All regressions include farm and year fixed effects. Standard errors are clustered at the farm level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

7 Pathways to Coexistence: The Role of Risk Management

7.1 The Buffering Effect of Landscape Features

Given the deterrent effect of pesticide EEEs, I evaluate whether they can be mitigated by physical landscape features (Section 3.4 Hypothesis 3). I examine if the *ex-ante* presence of planted hedgerows, which are natural barriers known to intercept nonpoint source pollution, can buffer parcels from exposure and thus moderate its impact on the development of organic farming. To do so, I decompose the EEE index into two components: exposure from neighboring parcels that is intercepted by a hedgerow along the contamination pathway ($\theta_{i,\text{blocked}}$) and exposure that reaches the focal parcel unimpeded ($\theta_{i,\text{unblocked}}$).

The results confirm that hedgerows provide meaningful but incomplete protection (Table 6). Across Columns (1)-(3), the marginal effect of unblocked exposure is consistently larger in magnitude than that of blocked exposure. In the municipality fixed-effects model (Column 3), the coefficient on unblocked exposure is -0.018, compared to -0.013 for blocked exposure. The difference ($\Delta = -0.006$, or approximately 6% of the mean organic rate) is statistically significant at the 1% level and negative, confirming a buffering effect.

Overall, these findings provide support for Hypothesis 3. Strategically-positioned hedgerows mitigate pesticide externalities, reducing the deterrent effect by approximately 28% (Column 3). However, the persistence of a significant negative effect even for blocked exposure ($\theta_{i,\text{blocked}}$) underscores that physical barriers alone cannot fully resolve the coexistence problem in mixed farming landscapes. The attenuation of the differential effect in the farm and parcel fixed-effects models Columns (4)-(5) reflects the time-invariant nature of hedgerows. Their protective benefits are predominantly cross-sectional. Once parcel-specific landscape characteristics are absorbed by fixed effects, limited temporal variation in the presence of *ex-ante* hedgerows constrains identification of within-parcel buffering effects.

7.2 The Moderating Role of Insurance

If farmers cannot use inputs to defend against exposure, do formal risk management tools alter their decisions? To test this, I offer a new perspective on how crop insurance, as a proxy for financial risk management, mediates the relationship between pesticide EEEs and organic management. I re-estimate the baseline specification (Equation 7) within subsamples defined by insurance status.

Figure 5 pinpoints the adverse effect of pesticide externalities. It falls entirely on

Table 6: Mitigation Effect of Hedgerows

	Dependent variable: Organic				
	Fixed effects				
	No FE	Dep. + year	Commune +year	Farm + year	Parcel + year
	(1)	(2)	(3)	(4)	(5)
Pesticide EEE index: unblocked	-0.019***	-0.019***	-0.018***	-0.000***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pesticide EEE index: blocked	-0.016***	-0.015***	-0.013***	-0.001***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ ($\theta_{i,\text{unblocked}} - \theta_{i,\text{blocked}}$)	-0.003***	-0.005***	-0.006***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ (% mean)	-3.1	-4.8	-5.6	0.4	0.2
Mean dependent variable	0.098	0.098	0.098	0.098	0.098
Observations	38,942,385	38,942,385	38,942,385	38,942,385	38,942,385
R^2	0.094	0.108	0.201	0.862	0.947

Notes: EEE indices are standardized by the common SD of total exposure (θ_i) so that $\theta_{i,\text{unblocked}}$ and $\theta_{i,\text{blocked}}$ are on the same scale. The 'blocked' EEE index ($\theta_{i,\text{blocked}}$) represents contamination from source to the first hedgerow encountered along wind and slope vectors, while 'unblocked' exposure $\theta_{i,\text{unblocked}}$ captures residual contamination beyond this barrier. Mean blocked share (over parcels): 0.526. All specifications include the full set of controls for agronomic and climatic conditions, knowledge- and market-based peer effects, and intrinsic parcel characteristics. Standard errors clustered at the farm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

uninsured farmers, who exhibit a large, statistically significant negative response. Specifically, this uninsured group experiences a 0.3 pp reduction in their probability of being organic for each one-unit increase in pesticide externalities. For insured farmers, however, the deterrent effect is entirely absent, with coefficients statistically indistinguishable from zero. This finding corroborates Hypothesis 4 (Section 3.4), demonstrating that the impact of EEEs is attributable to financial constraints. The mere presence of a financial safety net neutralizes this sensitivity, acting as a driver for organic adoption in an incomplete market setting where any coexistence loss is privately borne.

8 Discussion and Conclusion

The empirical results presented support my theoretical predictions (Section 3). Using administrative panel data on 9.5 million parcels and exploiting quasi-random variation from wind and topography, this paper provides micro-level evidence that pesticide externalities drive landscape-level coordination failures. These failures prevent the spatial agglomeration necessary to internalize exposure and support the organic sector. By simultane-

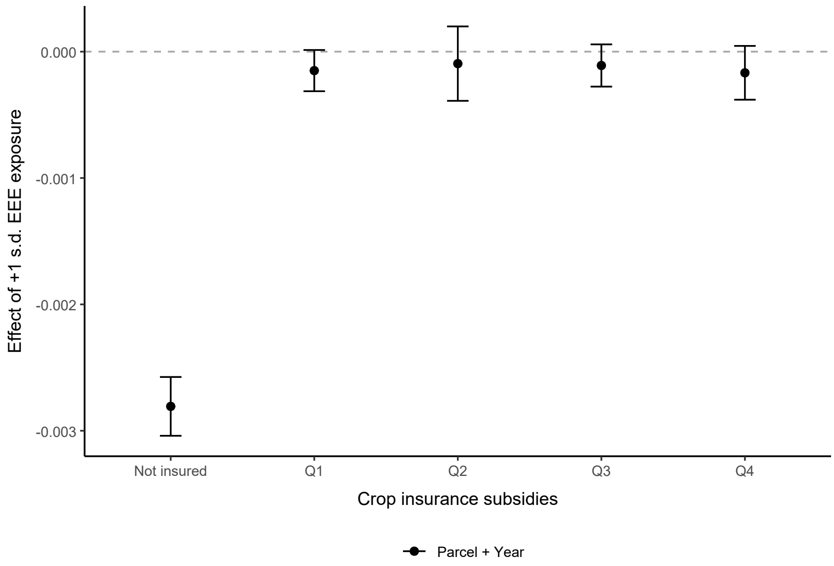


Figure 5: Financial risk management - Subsidized crop insurance

ously identifying endogenous, contextual, and correlated effects, I present novel insights into the interplay between physically-mediated externalities, 'Marshallian' spillovers, and market structure in shaping agricultural technology adoption. In particular, I show that EEEs significantly deter organic farming, thereby driving spatial sorting and preventing the emergence of clusters. Mitigation operates through two distinct channels, namely a physical one, where *ex-ante* hedgerows provide partial mitigation (boosting adoption by 28%), and a financial one, where insurance coverage neutralizes the potential loss related to involuntary decertification.

I also document the underlying economic mechanisms and find that this deterrent effect stems directly from the organic-conventional interface, rather than reflecting general agglomeration economies or spatially correlated unobservables. Neighboring pesticide applications create a fundamental trade-off for organic fields by reducing pest pressure at the cost of a certification dilemma. This reliance on neighbors' pesticides creates a triad of risks for organic farms regarding decertification (if audits reveal yield dependence on prohibited inputs), price premium erosion (if consumers perceive the system as non-autonomous, see e.g., Crowder and Reganold, 2015), and transition uncertainty (if conventional neighbors reduce pesticide use due to regulatory changes). These forwardlooking concerns, more so than immediate contamination, provide a strong rationale for the spatial avoidance documented in this analysis. The contamination-revelation mechanism thus operates through both direct financial channels and induced spatial selection.

This analysis is, however, subject to several limitations. The EEE index is a proxy, not a direct measure, of contamination. While it incorporates key biophysical channels, validating it with plot-level application data or residue testing remains an important avenue for future work. Additionally, causal inference in the mitigation analysis is limited by potential selection bias, as these adoption decisions are endogenous. Stronger identification would require quasi-experimental variation in, for instance, insurance availability. This analysis is limited to the private costs for organic farmers, leaving broader social welfare implications and optimal policy design as open questions. General equilibrium modeling of landscape-level policies could bridge this gap, assessing costs and benefits and identifying optimal spatial configurations.

More broadly, this study highlights that agricultural transitions are fundamentally spatial coordination problems, not just individual ones. Overcoming landscape lock-in requires policies that explicitly manage the externalities arising at field edges. These findings directly inform several policy implications. First, policies that solely subsidize organic conversion are miscalibrated. They ignore the fundamental coordination failure – i.e., the unpriced externality from conventional neighbors – and focus instead on the symptom. The core policy challenge is not adoption, but managing the interface between farming systems. Second, the heterogeneity in exposure mechanisms renders uniform national approaches suboptimal. Effective policy must be spatially targeted, for instance through organic priority areas or dynamic, topography-based buffer zones. Finally, my additional finding that hedgerows provide meaningful mitigation highlights a cost-effective, landscape-scale intervention: promoting ecological barriers, which simultaneously offers protection and biodiversity co-benefits.

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A Measuring Pesticide Externalities

In this paper, I focus on the management of agricultural parcels in a context of coexistence. While cross-parcel pesticide drifts are well documented in the literature, it remains unclear whether these hazards affect pesticide use decisions or technology adoption. For each potential emitter j in the r-radius neighborhood $B_r(i)$ we define a directed dose

$$\underset{\substack{i \in P_t,\ j \in P_{t-1} \\ j \in B_k(i)}}{\boldsymbol{\Theta}_{ij}} = w_{ij} a_j D_{jt-1} d_{ij}^{-\delta}, \qquad \text{where } w_{ij} = D_{ij}^{W} D_{ij}^{S} \Gamma_{ij} \tag{9}$$

From a biophysical perspective, the matrix $\boldsymbol{\Theta}_{ij}$ combines four components: an atmospheric and hydrological transport model, the intrinsic characteristics of the pollution source, the vulnerability of the receiving parcel, and the distance between the source and the receptor.

First, I account for *wind-mediated spillovers.* Pollutants such as fine particles (for instance, pesticide droplets) can travel via wind. If parcel j lies in the upwind direction of parcel i, using the meteorological convention, the emissions from j may reach i. The variable D_{ij}^{W} is a binary indicator denoting whether j is upwind relative to i. I identify upwind parcels using both the recorded wind direction of j (that is, the prevailing wind to which i is exposed) and the angle between the line $j \to i$ and a chosen reference. I compute the mean wind direction from the u- and v-components of the wind during j's spray window between year $(t-1)$ and $(t-5)$ (relative to parcel i).

Second, the indicator incorporates *topographical effects.* Hydrological flow and pollutant-transfer models show that in agricultural regions, a significant share of runoff and associated pollutants may migrate downhill, accumulate in downstream soils or aquifers, and potentially contaminate water resources. The term D_{ij}^{S} equals 1 if parcel j is uphill than i, allowing water to flow from j to i.

In addition, *gravity* is the key driving force behind surface runoff and the transport of soluble or particulate contaminants. A steeper slope accelerates the flow of sediments that may carry pesticide residues or other pollutants. Our model incorporates this effect with the term Γ_{ij}, defined as the gravitational force parallel to the slope. This variable is equal to $g\sin(\alpha)$, where $g \approx 9.81$ m/s^2 is the gravitational acceleration in the Earth surface, and α is the slope angle. The steeper the slope from j to i, the faster contaminants are driven downhill. If j is not upslope than i, then Γ_{ij} is null, since gravity will not naturally transport pollutants upslope.

Third, I take into account *pesticide use*. In absence of data on the quantity of pesticide applied at the parcel level, I refer directly on the production system. The term D_{jt-1} equals one if parcel j is under conventional production system. I assume that parcel j does not apply pesticides if it is under organic management or extensive crop. I weight the index by parcel size to take into account the fact that larger source parcels are expected to contribute proportionally more pesticide. The variable a_j assumes that pesticide application (and therefore potential transfer) scales linearly with the area of the source parcel, which is a reasonable assumption for most agricultural practices.

Finally, the function $d_{ij}^{-\delta}$ imposes a *distance-based attenuation* that reflects the fact that pesticide concentrations generally diminish with increasing distance through dilution, degradation, or dispersal processes. To test the best specification, I calibrate a gravitational and exponential specification with varying parameters using a grid search approach. For example, I systematically test a range of values for the exponential specification from 0.005 to 0.02 in increments of 0.0025 by estimating a logistic and probit regression model for each value and computing the AIC and BIC information criteria. This grid search calibration, which provides a rigorous evaluation of model performance, is consistent with empirical approaches used in gravity models for international trade (Anderson and Van Wincoop, 2003) and in spatial econometrics (Fotheringham et al., 2000; LeSage and Pace, 2009). The calibration results reveal that the exponential specification with a decay parameter of 0.005 (or 0.01 as a second best) yield the lowest AIC and BIC values, and then offer an optimal balance between model fit and parsimony.

Using an exponential specification, commonly used in spatial economics and exposure-flow models, imply that the larger the value of δ, the more rapidly the influence of past observations diminishes. For robustness checks, we perform sensibility analyses using both values, and also perform robustness checks using the most optimal value for gravitational specification.

Because this indicator is multiplicative, if any condition does not hold, then the risk contribution from that source is zero. In other words, the pathway for drift or runoff is assumed inoperative (or very minimized) under those circumstances.

For isolating the aggregated effect of pesticide externalities generated by i's neighbor, I compute each year a parcel-level index, θ_i, as defined in Equation (1).

B Additional Tables

Table B1: Description of selected variables

Variables	Description	Source
	Panel A: Outcome variable	
Organic farming	Binary variable indicating if the parcel is managed under organic farming	LPIS[a]
Organic conversion	Binary variable equal to 1 if a parcel switches from conventional to organic at time t	LPIS
Organic deconversion	Binary variable equal to 1 if a parcel switches from organic to conventional at time t	LPIS
Isolated	Binary variable equal to 1 when the parcel has no organic neighbors	LPIS
	Panel B: Peer effects	
	Endogenous peer effects (θ_{it})	
Pesticide EEE index (raw)	Pesticide EEE index as defined in Section 3.1 from neighbor's pesticide use, based on practices (organic/non-organic), wind patterns, and topography at time $(t-1)$ and around radius k	LPIS, ERA5 Reanalysis, BD ALTI®
Pesticide EEE index (total, scaled)	Total raw pesticide EEE index, demeaned and divided by the raw EEE standard deviation	LPIS, ERA5 Reanalysis, BD ALTI®
Pesticide EEE index (unblocked, scaled)	Component of the EEE index representing residual contamination passing beyond the first barrier (i.e., a hedgerow)	LPIS, ERA5 Reanalysis, BD ALTI®, BD TOPO®
Pesticide EEE index (blocked, scaled)	Component of the EEE index representing contamination from the source to the first barrier	LPIS, ERA5 Reanalysis, BD ALTI®, BD TOPO®
	Exogenous peer effects ($\mathbf{Z}'_{it}$)	
Neighbor UUA with similar crop	Total utilized agricultural area (in ha) of neighboring parcels cultivated with the same crop group as the focal parcel around radius k	LPIS
Farmer operational network	Proxy for social interaction, measured as the count of distinct peers whose own operational area (defined by municipalities of headquarter and parcels) overlaps with the focal farmer's operational area	LPIS
Total peers in neighborhood	Total count of distinct farmers located within the defined neighborhood k	LPIS
	Correlated peer effects ($\mathbf{W}'_{it}$)	
Tick-market externalities	Count of organic cooperatives within a 10km radius, by type of activity, as a proxy for shared market access	Agence Bio
Importation	Number of organic cooperatives specialized in importation	
Distribution	Number of organic cooperatives specialized in distribution	
Processing	Number of organic cooperatives specialized in processing	
Restaurant	Number of organic cooperatives specialized in restaurants	
Storage	Number of organic cooperatives specialized in storage	
Transport	Number of organic cooperatives specialized in transport	
	Panel C: Additional parcel-level covariates ($\mathbf{X}'_{it}$)	
Parcel size	UUA of the focal parcel (in ha)	LPIS[a]
Own farm UUA	Total UAA (in ha) belonging to the focal parcel's farmer within the defined neighborhood	LPIS
Mean temperature	Mean temperature (°C) calculated over the five years prior to time t	ERA5 Reanalysis
Mean rainfall	Mean rainfall (mm) calculated over the five years prior to time t	ERA5 Reanalysis
	Panel D: Farm-level data ($\mathbf{X}'_{ft}$)	
Yield	Farm-level yield, in standard deviation units	FADN[a]
Pesticide expenses	Farm-level total expenses on pesticides (in €)	FADN[a]
Fertilizer expenses	Farm-level total expenses on fertilizers (in €)	FADN[a]
Organic farming	Dummy variable indicating if the farm is certified organic	LPIS

Notes: [a] With the exception of these variables, all others are the author's calculations based on the datasets sourced.

C Robustness Checks

C.1 Main results at the parcel level (Section 5.1)

In this section, I discuss the results obtained for robustness checks regarding the main analysis. Similar results are obtained from the main estimate when control variables are excluded (Table C2 Panels A-B) and alternative standard error clusterings are used at the commune, department, or two-way farm-year levels (Table C2 Panel C). The coefficient remains statistically significant at the 1% level with nearly all clustering approaches. Next, I verify that the findings are not driven by misspecification of the functional form. For tractability due to the large dataset, I estimate a linear probability model in Section 4.2, which serves as a first-order approximation of the non-linear contamination probability. As a robustness check, I test for nonlinearities using year-by-year subsamples. As shown in Figure C1, the coefficients from the LPM are nearly identical to those from the Logit and Probit models. This consistency validates the stability of the results across the sample period, indicating that they are not influenced by any single year or pandemic-related disruptions. I also explore the dose-response relationship and the construction of the EEE index. Table C2 Panel D discretizes the EEE index into quintiles, and highlights a clear monotonic dose-response pattern. Relative to the lowest exposure quintile (Q1), coefficients become progressively more negative from Q2 to Q5. This nonlinearity points to threshold effects that are consistent with certification-threatening risks.

Additionally, Table C3 confirms that the main findings are robust to raw EEE index and alternative spatial decay parameters, across specifications with $\delta \in \{0.0025, 1\}$.

I further test the robustness of the heterogeneity analysis by controlling for alternative fixed effects (Figures C2-C5), as well as the robustness of the hedgerow analysis (Table C4).

Table C2: Robustness checks - Baseline model

	Dependent variable: Organic				
	Fixed effects				
	No FE	Dep. + year	Commune +year	Farm + year	Parcel + year
	(1)	(2)	(3)	(4)	(5)
	Panel A: No covariates				
Pesticide EEE index	-0.0175***	-0.0174***	-0.0160***	-0.0004***	-0.0026***
	(0.0003)	(0.0003)	(0.0002)	(0.0000)	(0.0001)
R^2	0.0910	0.1080	0.2000	0.8620	0.9470
	Panel B: Without the variable SameCrop				
Pesticide EEE index	-0.0173***	-0.0173***	-0.0161***	-0.0005***	-0.0027***
	(0.0003)	(0.0003)	(0.0002)	(0.0000)	(0.0001)
R^2	0.0930	0.1080	0.2010	0.8620	0.9470
	Panel C: Different sd. errors clusterings				
	Cluster at the commune level				
Pesticide EEE index	-0.0175***	-0.0174***	-0.0161***	-0.0005***	-0.0027***
	(0.0003)	(0.0003)	(0.0003)	(0.0000)	(0.0001)
R^2	0.0940	0.1080	0.2010	0.8620	0.9470
	Cluster at the department level				
Pesticide EEE index	-0.0175***	-0.0174***	-0.0161***	-0.0005***	-0.0027***
	(0.0018)	(0.0015)	(0.0015)	(0.0002)	(0.0004)
R^2	0.0940	0.1080	0.2010	0.8620	0.9470
	Two-way clustering at the farm and year				
Pesticide EEE index	-0.0175***	-0.0174***	-0.0161***	-0.0005	-0.0027*
	(0.0014)	(0.0013)	(0.0011)	(0.0003)	(0.0014)
R^2	0.0940	0.1080	0.2010	0.8620	0.9470
	Panel D: Non-linear effects				
	Quintile specification[1]				
Pesticide EEE index: Q2	-0.0450***	-0.0407***	-0.0287***	-0.0017***	-0.0036***
	(0.0008)	(0.0008)	(0.0005)	(0.0001)	(0.0002)
Pesticide EEE index: Q3	-0.0588***	-0.0546***	-0.0437***	-0.0024***	-0.0065***
	(0.0009)	(0.0009)	(0.0006)	(0.0001)	(0.0003)
Pesticide EEE index: Q4	-0.0730***	-0.0687***	-0.0575***	-0.0028***	-0.0094***
	(0.0010)	(0.0010)	(0.0007)	(0.0001)	(0.0003)
Pesticide EEE index: Q5	-0.0877***	-0.0845***	-0.0741***	-0.0027***	-0.0120***
	(0.0011)	(0.0010)	(0.0008)	(0.0002)	(0.0004)
R^2	0.0990	0.1130	0.2030	0.8620	0.9470
	Quadratic specification				
Pesticide EEE index	-0.0183***	-0.0183***	-0.0170***	-0.0005***	-0.0029***
	(0.0004)	(0.0004)	(0.0003)	(0.0000)	(0.0001)
Pesticide EEE index: squared	0.0001**	0.0001**	0.0001**	0.0000**	0.0000**
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
R^2	0.0940	0.1080	0.2010	0.8620	0.9470

Notes: Dependent variable is a dummy equal to 1 if parcel i is managed organically in year t. The pesticide EEE index is standardized (mean-centered and scaled to unit variance), and results are interpreted as the effect of a one standard deviation increase. Raw exposure values range from 0 to 874.406 with mean 1.755 and standard deviation 2.927. All specifications include the full set of controls for agronomic and climatic conditions, knowledge- and market-based peer effects, and intrinsic parcel characteristics. [1]The reference category for the discretized EEE index corresponds to the first quintile. Standard errors clustered at the farm level are reported in parentheses (except for Panel C). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C3: Robustness checks - Different definitions of EEEs

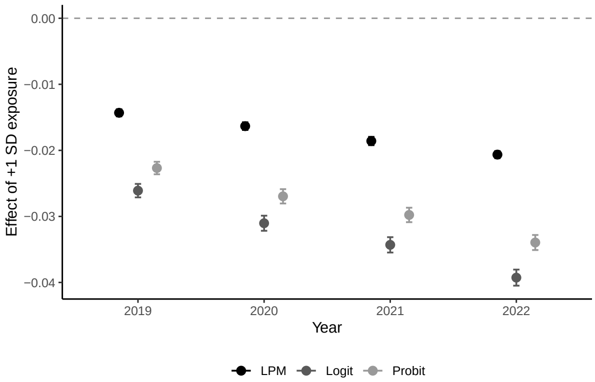
	Dependent variable: Organic				
	Fixed effects				
	No FE	Dep. + year	Commune +year	Farm + year	Parcel + year
	(1)	(2)	(3)	(4)	(5)
	Panel A: Raw pesticide EEE index				
Pesticide EEE index	-0.0060***	-0.0059***	-0.0055***	-0.0002***	-0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
R^2	0.0940	0.1080	0.2010	0.8620	0.9470
	Panel B: Alternative spatial decay parameters δ				
	$\delta = 0.0025$				
Pesticide EEE index	-0.0171***	-0.0170***	-0.0157***	-0.0005***	-0.0032***
	(0.0003)	(0.0003)	(0.0002)	(0.0000)	(0.0001)
R^2	0.0940	0.1080	0.2000	0.8620	0.9470
	$\delta = 0.01$				
Pesticide EEE index	-0.0167***	-0.0166***	-0.0154***	-0.0004***	-0.0020***
	(0.0003)	(0.0003)	(0.0003)	(0.0000)	(0.0001)
R^2	0.0930	0.1080	0.2000	0.8620	0.9470
	$\delta = 0.015$				
Pesticide EEE index	-0.0158***	-0.0157***	-0.0145***	-0.0004***	-0.0017***
	(0.0003)	(0.0003)	(0.0003)	(0.0000)	(0.0001)
R^2	0.0930	0.1080	0.2000	0.8620	0.9470
	$\delta = 0.02$				
Pesticide EEE index	-0.0152***	-0.0151***	-0.0138***	-0.0003***	-0.0015***
	(0.0003)	(0.0003)	(0.0003)	(0.0000)	(0.0001)
R^2	0.0930	0.1080	0.2000	0.8620	0.9470
	$\delta = 0.05$				
Pesticide EEE index	-0.0137***	-0.0135***	-0.0123***	-0.0002***	-0.0012***
	(0.0004)	(0.0004)	(0.0003)	(0.0000)	(0.0001)
R^2	0.0920	0.1070	0.2000	0.8620	0.9470
	$\delta = 0.1$				
Pesticide EEE index	-0.0129***	-0.0127***	-0.0115***	-0.0001***	-0.0011***
	(0.0004)	(0.0004)	(0.0004)	(0.0000)	(0.0001)
R^2	0.0920	0.1070	0.2000	0.8620	0.9470
	$\delta = 0.25$				
Pesticide EEE index	-0.0119***	-0.0116***	-0.0105***	0.0000	-0.0009***
	(0.0004)	(0.0004)	(0.0004)	(0.0000)	(0.0001)
R^2	0.0920	0.1070	0.1990	0.8620	0.9470
	$\delta = 0.5$				
Pesticide EEE index	-0.0112***	-0.0109***	-0.0099***	0.0001***	-0.0008***
	(0.0003)	(0.0003)	(0.0003)	(0.0000)	(0.0000)
R^2	0.0920	0.1070	0.1990	0.8620	0.9470
	$\delta = 1$				
Pesticide EEE index	-0.0110***	-0.0106***	-0.0097***	0.0001***	-0.0007***
	(0.0003)	(0.0003)	(0.0003)	(0.0000)	(0.0000)
R^2	0.0920	0.1060	0.1990	0.8620	0.9470

Notes: Dependent variable is a dummy equal to 1 if parcel i is managed organically in year t. The pesticide EEE index is standardized (mean-centered and scaled to unit variance), and results are interpreted as the effect of a one standard deviation increase. All specifications include the full set of controls for agronomic and climatic conditions, knowledge- and market-based peer effects, and intrinsic parcel characteristics. Standard errors clustered at the farm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

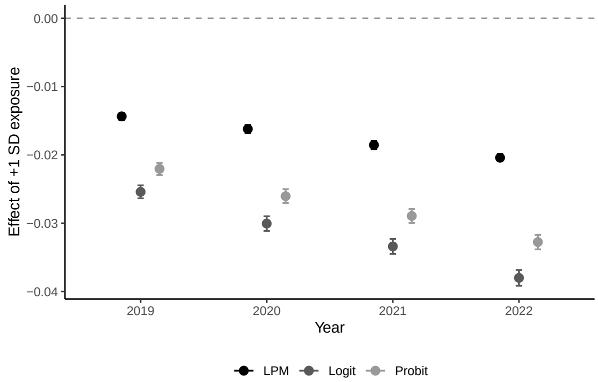
Table C4: Robustness checks - Mitigation Effect of Hedgerows

	Dependent variable: Organic				
	Fixed effects				
	No FE	Dep. + year	Commune +year	Farm + year	Parcel + year
	(1)	(2)	(3)	(4)	(5)
	Panel A: Raw EEE index θ				
Pesticide EEE index: unblocked	-0.006***	-0.007***	-0.006***	0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pesticide EEE index: blocked	-0.005***	-0.005***	-0.004***	0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ $(\theta_{i,\text{unblocked}} - \theta_{i,\text{blocked}})$	-0.001	-0.002	-0.002	0.000	0.000
Mean dependent variable	0.098	0.098	0.098	0.098	0.098
Observations	38,942,385	38,942,385	38,942,385	38,942,385	38,942,385
R^2	0.094	0.108	0.201	0.862	0.947
	Panel B: Year-specific common standard deviation				
Pesticide EEE index: unblocked	-0.019***	-0.019***	-0.018***	-0.000***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pesticide EEE index: blocked	-0.016***	-0.015***	-0.013***	-0.001***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ $(\theta_{i,\text{unblocked}} - \theta_{i,\text{blocked}})$	-0.003	-0.005	-0.006	0.000	0.000
Mean dependent variable	0.098	0.098	0.098	0.098	0.098
Observations	38,942,385	38,942,385	38,942,385	38,942,385	38,942,385
R^2	0.094	0.108	0.201	0.862	0.947

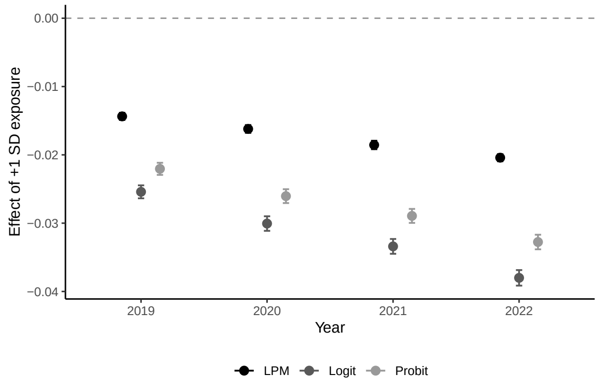
Notes: Dependent variable is a dummy equal to 1 if parcel i is managed organically in year t. The EEE index is standardized (mean-centered and scaled to unit variance), and results are interpreted as the effect of a one standard deviation increase. Raw exposure values range from 0 to 874.406 with mean 1.755 and standard deviation 2.927. All specifications include the full set of controls for agronomic and climatic conditions, knowledge- and market-based peer effects, and intrinsic parcel characteristics. Standard errors clustered at the farm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.



(a) No FE

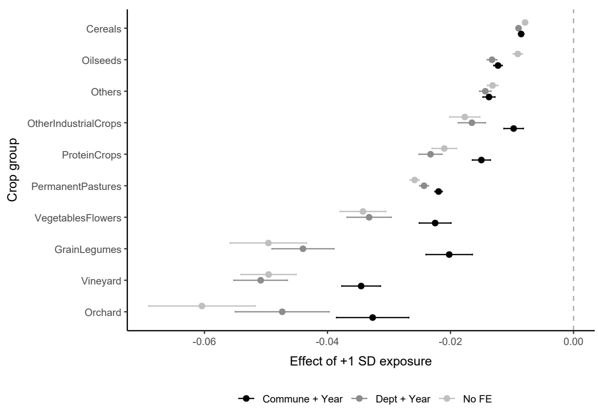


(b) Municipality FEs

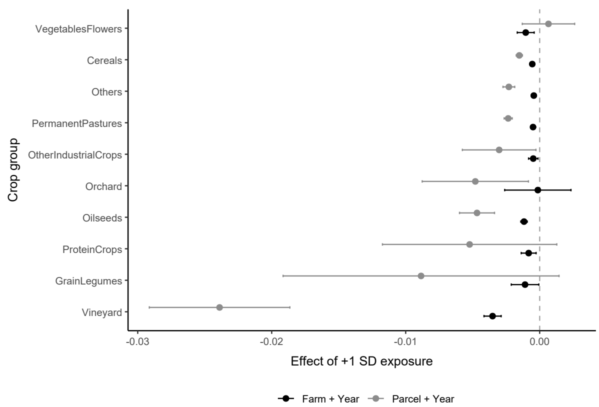


(c) Department FEs

Figure C1: Robustness checks - Year-by-year effect of exposure on organic farming

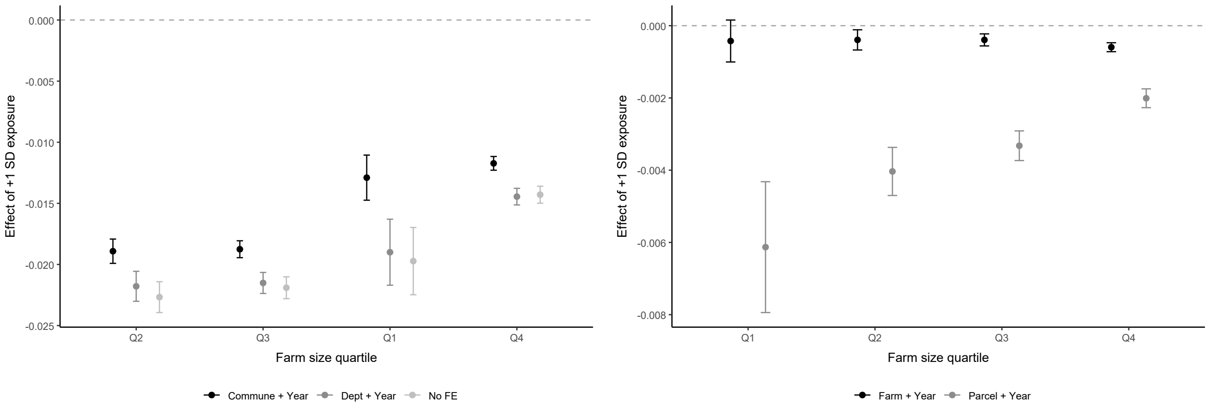


(a) No FE vs municipality vs department FEs



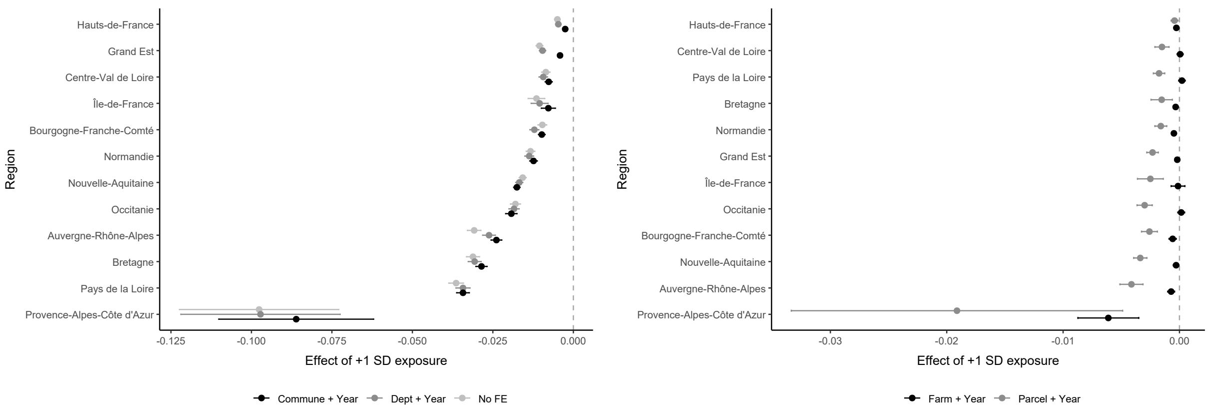
(b) Farm vs parcel FEs

Figure C2: Robustness checks - Heterogeneity analysis by crop type



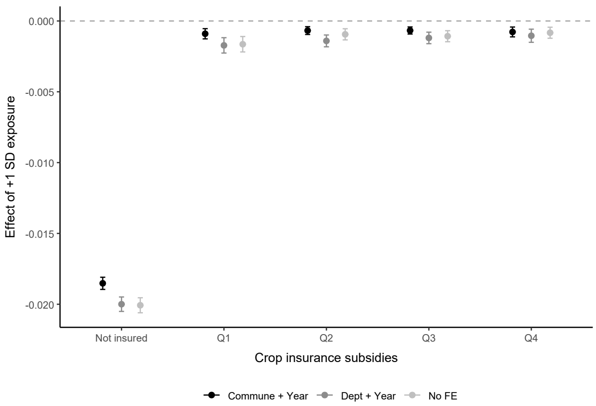
(a) No FE vs municipality vs department FEs (b) Farm vs parcel FEs

Figure C3: Robustness checks - Heterogeneity analysis by farm size

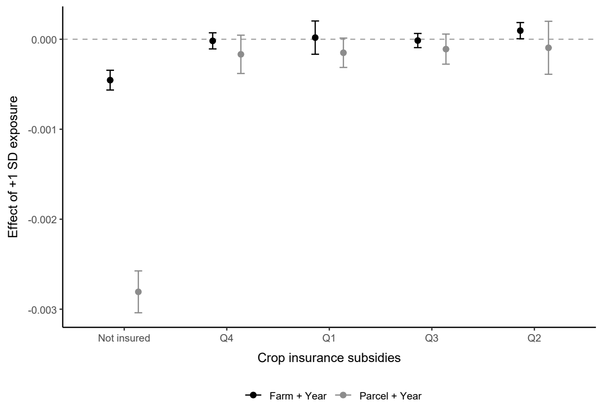


(a) No FE vs municipality vs department FEs (b) Farm vs parcel FEs

Figure C4: Robustness checks - Heterogeneity analysis by region



(a) No FE vs municipality vs department FEs



(b) Farm vs parcel FEs

Figure C5: Robustness checks - Financial risk management instrument

C.2 Main results at the farm level (Section 6)

In this section, I test the robustness of the economic results using different clustering specifications.

Table C5: Robustness checks (inference) - Effects on normalized yields

	Dependent variable: Yields (normalized)								
	All farms			Conventional			Organic		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pesticide EEE index	0.030	0.030	0.030	0.011	0.010	0.010	0.206**	0.206*	0.206*
	(0.025)	(0.031)	(0.026)	(0.026)	(0.033)	(0.024)	(0.064)	(0.111)	(0.089)
Organic	-0.420**	-0.420**	-0.420**						
	(0.111)	(0.126)	(0.115)						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Farm×year	Mun.	Dep.	Farm×year	Mun.	Dep.	Farm×year	Mun.	Dep.
Observations	20,830	20,830	20,830	18,443	18,443	18,443	2,387	2,387	2,387
R^2	0.480	0.480	0.480	0.488	0.488	0.488	0.499	0.500	0.500

Notes: $\bar{\theta}_{f(t-1)}$ is the average of parcel-level EEE index at the farm level. *Organic* represents farms with at least one parcel certified under organic. All regressions include farm fixed effects and year fixed effects. Standard errors are clustered at the municipality (mun.) or department (dep.) level, or two-way (farm×year). *p<0.1; **p<0.05; ***p<0.01