



Drivers of pesticide expenditure on Italian farms: evidence from a multi-stage FADN panel analysis

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ABSTRACT

The wine sector is operating under increasing pressure from a fundamental policy trade-off: reconciling the drive for high economic performance with the stringent sustainability objectives set by the Common Agricultural Policy. In this light, this study aims to identify the main causal drivers of pesticide expenditure and quantify the influence of farms' structural and economic characteristics on this spending. Utilising Farm Accountancy Data Network (FADN) panel data for the period 2019–2023, a multi-stage methodological approach was adopted. K-means cluster analysis reveals a pronounced structural polarisation: approximately 10% of farms, characterised by an intensive high-input model, account for most of the expenditure. The fixed effects regression results demonstrate that the production intensification model is the most significant and unequivocal driver of pesticide expenditure. Dynamic interaction terms further reveal significant heterogeneity: smaller farms (<15 ha) and farms located in Central Italy display the fastest annual growth in pesticide expenditure. A marked contraction in 2022, followed by a rebound in 2023, highlights the sector's vulnerability to macroeconomic shocks. The robust evidence of a strong structural polarisation, defined by the significant and unequal contribution of the intensive model to overall pesticide expenditure, demands a paradigm shift in policy design.

1. Introduction

The transition towards more sustainable agricultural systems has become one of the main priorities of European agricultural policy. In recent years, rising environmental concerns, climate change, biodiversity loss, and growing societal demand for safer food production have profoundly reshaped the European Union (EU) policy agenda. Within this context, the European Green Deal and the Farm to Fork Strategy have established an ambitious roadmap to transform European agriculture into a more resilient, resource-efficient, and environmentally sustainable sector. One of the most important objectives is the commitment to reduce the use and risk of synthetic pesticides by 50% by 2030 while simultaneously preserving farm productivity, food security, and the economic viability of agricultural businesses. This goal is particularly challenging because pesticide use is not only an environmental concern but also a major component of production costs and, consequently, a determinant of farm economic efficiency [1–3]. In fact, pesticide reduction may generate substantial adjustment costs and negatively affect profitability in some sectors [4], while upstream inputs such as fertilizers and pesticides remain significant contributors to the

environmental footprint of agri-food supply chains [5]. Intensive agricultural production remains structurally dependent on pesticide inputs, which support productivity and economic performance while generating substantial external costs for human health and the environment [6,7]. Meeting pesticide-reduction targets, including those established by the Farm to Fork Strategy, therefore requires integrated practices and management approaches capable of reducing this dependence without compromising crop productivity or farm economic viability [8–10].

In this context, pesticide use is increasingly interpreted as the outcome of interconnected drivers, including agricultural practices, environmental policies, climate change, and farm-level decision-making [11]. Viticulture represents a particularly relevant case, as vineyards are highly vulnerable to fungal and bacterial pathogens and have traditionally required intensive phytosanitary management [12–14]. At the same time, concerns about biodiversity, environmental quality, human health, and consumer perceptions have intensified the search for more sustainable wine production systems [8,15,16]. Climate change further complicates pesticide management by increasing pathogen pressure and production uncertainty, thereby raising the demand for phytosanitary treatments and potentially reducing technical efficiency [17–19].

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Although integrated pest management, precision agriculture, digital monitoring systems, and agronomic innovations may improve input-use efficiency and reduce pesticide dependence [20,21], their adoption may increase production and investment costs and require substantial changes to farm organisational structures and management practices, especially for smaller farms [17,22,23].

Beyond the farm-level and technological dimensions discussed above, recent studies on sustainable development and environmental governance further argue that achieving sustainability objectives requires coordinated policy frameworks integrating environmental regulation, public expenditure, and institutional quality [24–26]. Consequently, pesticide-reduction policies cannot rely on uniform assumptions because pesticide use and the economic consequences of sustainable pest-management practices can vary with farm size, production intensity, managerial capacity, technological adoption, local environmental conditions, actor-specific barriers, uncertainty, and the interaction between scientific evidence, policy design, and farming practices [27,28].

In this paper, the term “pesticides” is used in a broad sense to refer to pesticide-related farm expenditure recorded in the FADN data.

The central research issue addressed in this study is to explain how structural farm characteristics shape pesticide expenditure over time and whether these relationships differ across heterogeneous wine farms. As discussed above and supported by the existing literature, pesticide expenditure reflects the interaction of multiple factors, including production intensity, farm economic performance, technological capacity, territorial conditions, climate-related pest pressure, and policy incentives. It should therefore be interpreted not merely as a short-term managerial decision, but as the outcome of structural farm characteristics and broader economic and environmental conditions. This perspective motivates the need for farm-level evidence capable of identifying which types of farms are most exposed to pesticide expenditure growth and the factors underlying this trend.

Italy represents an especially appropriate case study because its wine sector combines high economic relevance with strong structural and territorial heterogeneity. Farms differ markedly in size, production systems, pedoclimatic conditions, market orientation, and organisational models. This diversity makes it possible to examine whether pesticide expenditure is driven by homogeneous sector-wide forces or by differentiated farm typologies and territorial dynamics.

The relevant literature can be organised into four main strands. The first strand focuses on sustainability policy and environmental governance, showing that pesticide reduction is embedded in broader institutional frameworks linking agricultural policy, public expenditure, environmental regulation, and sustainable development objectives. Studies on green budgeting, macro-policy determinants of environmental pressure, and sustainable development governance underline that environmental outcomes depend not only on farm-level decisions but also on the design and coherence of policy instruments.

A second strand examines pesticide use, pesticide expenditure, and farm economic performance. These studies emphasise the trade-off between reducing chemical inputs and preserving productivity, profitability, and technical efficiency. They are directly relevant to the first hypothesis, since they suggest that more economically performing or input-intensive farms may display higher pesticide expenditure because pesticide use is part of a broader production strategy aimed at preserving yield and product quality.

A third strand investigates technological innovation and input-use efficiency. Research on integrated pest management, precision agriculture, digital monitoring and decision-support systems shows that new technologies can reduce pesticide dependence or improve the efficiency of pesticide applications. However, these effects are not uniform because adoption depends on farm size, investment capacity, managerial skills and access to advisory services. This literature supports the expectation that farm typologies and structural characteristics condition pesticide expenditure dynamics.

A fourth strand focuses on farm heterogeneity and territorial effects. This literature shows that differences in farm size, production specialisation, geographical location, climate exposure and institutional context can influence input demand and environmental performance. It provides the theoretical basis for analysing whether pesticide expenditure varies across farm-size classes and geographical areas, as proposed in the third hypothesis.

Despite these contributions, the literature still leaves three related gaps. First, studies often examine policy pressures, pesticide use, technological innovation, or farm performance separately, whereas pesticide expenditure is likely to emerge from their interaction. Second, previous works frequently rely on aggregate indicators, cross-sectional comparisons, or direct pesticide-use measures, while less is known about farm-level expenditure dynamics observed over time. Third, limited evidence is available on how latent structural dimensions and farm typologies jointly explain pesticide expenditure in heterogeneous wine-producing systems. These gaps matter because pesticide-reduction policies can be inefficient if they do not distinguish between farms that differ in production intensity, size, economic structure and territorial context.

Building on these gaps, this study interprets pesticide expenditure as the outcome of interactions among farm structure, production intensity, economic performance, technological capacity, and territorial heterogeneity (Fig. 1).

The conceptual framework gives rise to three testable hypotheses, each grounded in a specific theoretical and empirical strand of the agricultural economics literature.

The first hypothesis builds upon production economics and input-demand theory, which posit that farms allocate production inputs according to expected returns and production risk. More intensive and economically stronger production systems are therefore expected to invest more heavily in plant protection to preserve yield and product

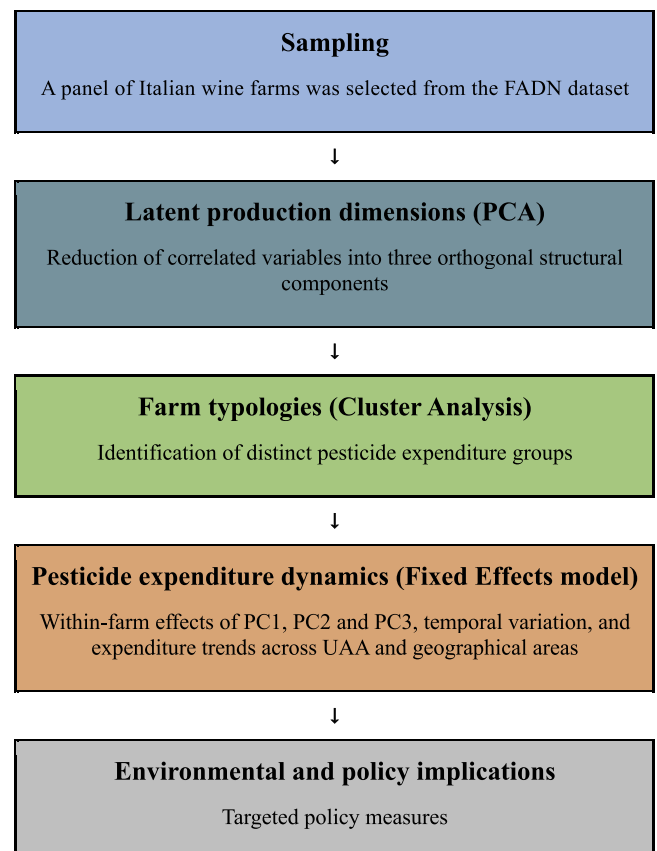


Fig. 1. Conceptual framework of the study.

quality. This theoretical expectation is supported by empirical studies showing positive relationships between production intensity, economic performance, and input use.

H1: Farm structural characteristics associated with higher production intensity and economic performance are positively related to pesticide expenditure.

The second hypothesis is grounded in the literature on farm heterogeneity and structural economics, which recognises that farms differ in resource endowments, managerial capabilities, production specialisation, and investment capacity. These structural differences influence production strategies and input-allocation decisions, suggesting that farms can be grouped into distinct latent typologies characterised by different pesticide expenditure patterns.

H2: Latent structural dimensions identify distinct farm typologies characterised by significantly different pesticide expenditure patterns.

The third hypothesis builds on regional agricultural economics and the literature on environmental heterogeneity, which argue that farm decision-making is shaped by local production conditions, climatic variability, and territorial characteristics. Consequently, the relationship between farm structural characteristics and pesticide expenditure is expected to vary across different geographical areas and farm-size classes.

H3: The effects of farm structural characteristics on pesticide expenditure vary according to farm size and geographical location.

To empirically examine these hypotheses, the study addresses the following research questions:

RQ1. What latent structural dimensions characterise Italian wine farms?

RQ2. How do these structural characteristics influence pesticide expenditure over time?

RQ3. To what extent do farm size and geographical location moderate pesticide expenditure dynamics?

The empirical strategy combines Principal Component Analysis to identify latent structural dimensions, fixed-effects panel estimation to assess their relationship with pesticide expenditure over time, and stratified analyses to evaluate differentiated patterns by farm size and geographical location.

This study aims to explain how the structural and economic characteristics of Italian wine farms shape pesticide expenditure over time. To this end, it identifies the latent dimensions underlying farm heterogeneity, distinguishes farm typologies with different expenditure profiles, and assesses whether these dynamics vary according to farm size and geographical location. By addressing these objectives, the study provides empirical evidence to support more targeted pesticide-reduction policies in the Italian wine sector.

The remainder of the paper is structured as follows. Section 2 presents the data and the multi-stage methodological framework. Section 3 reports the results of the PCA, clustering, and fixed effects panel model. Section 4 discusses the findings in light of current Common Agricultural Policy (CAP) priorities and outlines policy implications. Section 5 concludes and identifies avenues for future research.

2. Methodology

2.1. Sample collection

The empirical analysis utilised micro-level data sourced from the Italian Farm Accountancy Data Network (FADN). Specifically, the study

was conducted on a balanced panel of Italian wine-producing farms spanning the 2019–2023 period. Adopting a strict balanced panel criterion resulted in a final sample of 688 distinct firms observed across all five years, yielding a total of 3440 farm-year observations. Organic farms were excluded from the analysis. The geographical distribution of this final sample is summarised in Table 1.

The selection of explanatory variables was guided by the multidimensional nature of pesticide expenditure. Accordingly, the variables were chosen to capture the main economic, financial, production, and cost-related dimensions of farm management. In particular, the analysis includes indicators of farm economic performance (total company revenue, gross marketable production, added value, net company product, operating income, net income, farm net value added, and gross operating margin), which reflect the farm's capacity to generate income and may influence the intensity of input use. A second group of variables captures production costs and resource allocation decisions. Fertiliser expenses, mechanisation expenses, water, electricity and fuel expenses, variable costs, fixed costs, and salaries and social charges were included because they represent the principal categories of production expenditure and are closely associated with the technological and managerial intensity of farming systems. European Union subsidies were included in the analysis because they allow the assessment of whether public support is associated with changes in expenditure structures and production intensity. Pesticide expenses constitute the variable of primary interest. The variables selected are measured at the farm level as values per hectare. Finally, Utilised Agricultural Area (UAA) was included as a structural variable to assess its influence on pesticide expenditure. Table 2 reports the descriptive statistics for the economic and input variables used in the PCA, calculated as mean values per hectare over the 2019–2023 period. The consistently high standard deviations relative to the mean values indicate big structural and economic differences across farms, justifying the use of PCA to capture the main underlying dimensions of variability. All monetary variables are expressed in nominal terms and were not deflated over the 2019–2023 period. Therefore, the empirical results should be interpreted as reflecting changes in nominal farm-level expenditure rather than price-adjusted real expenditure.

2.2. Principal component analysis

The methodology's first stage involved applying PCA to the 15 variables detailed in Table 2. This step was essential to reduce the inherent collinearity and dimensionality of the variable set by distilling them into three latent, orthogonal components [29]. To enhance the interpretability of these components, the solution was subjected to varimax rotation with Kaiser normalisation. The first component (PC1) accounts for 59.3% of the total variance. Collectively, the three retained components successfully explain 78.9% of the total variability in the original dataset, confirming that the three-component solution is highly representative (Table 3).

The PCA loadings, obtained after varimax rotation, allow for the clear identification of three distinct latent dimensions underlying the firm's economic structure (Table 4). Component 1 (PC1) is identified as "Economic-financial performance" due to its high and dominant correlations with key profitability and revenue metrics. Specifically, PC1 exhibits the highest loadings for operating income (0.978), gross

Table 1
Area sample distribution (Italian wine farms, n=3440; 2019–2023).

Area	Percentage
Center	9.6
Northeast	40.8
Northwest	16.7
South and islands	32.8

Table 2

Descriptive statistics of key economic and input variables (Italian wine farms, n=3440; 2019–2023).

	Mean value (per hectare)	Standard deviation
Pesticide expenses	449.9	393.35
Total company revenue	9271.7	11733.57
Gross marketable production	8999.8	11346.09
European Union subsidies	252.4	421.18
Fertilizer expenses	285.0	322.33
Mechanization expenses	318.6	246.79
Water, electricity and fuel expenses	139.7	296.89
Added value	6447.4	8300.00
Net company product	5600.3	7882.47
Salaries and social charges	968.6	1394.73
Operating income	4466.6	7197.17
Net income	4844.0	10143.89
Variable costs	3167.6	4651.70
Fixed costs	1471.3	1806.95
Farm net value added	5953.7	8057.46
Gross operating margin	5478.8	7702.89

operating margin (0.946), net company product (0.944), and added value (0.913), making it a robust measure of overall firm success and income generation, consistent with the “farm performance/efficiency” factor found by other authors (e.g., [30,31]). Component 2 (PC2) is labelled “Production Costs and EU support” as it captures firm expenditure dynamics, showing high positive loadings on fixed costs (0.829), salaries and social charges (0.761), and water, electricity and fuel expenses (0.756). This dimension is also moderately correlated with European Union subsidies (0.347). Component 3 (PC3) is named “Production intensification model” and clearly defines the input-intensive nature of the firm, showing strong positive correlations with fertiliser expenses (0.783) and mechanisation expenses (0.768). The scores derived from these three orthogonal components were subsequently used as non-collinear explanatory variables in the k-means cluster analysis and fixed effects regression model.

The decision to retain three components was supported by the Kaiser criterion ($\lambda > 1$) and confirmed by the scree plot.

2.3. Clustering

In the second stage, k-means clustering was performed on the scores of these three principal components and the expenditure on pesticides (a variable not previously included in the PCA) [32]. The model aims to verify whether the mean scores of the three principal components are significantly different between the two identified clusters, controlling both for the intrinsic variability of each individual farm and for the evolution over time. The number of clusters was determined prior to the

final estimation using the average silhouette [33], after the optimal range was initially explored using the Bayesian information criterion. Only solutions yielding an average silhouette score above 0.50 were considered meaningful in terms of separation and cohesion. The two-cluster solution was therefore selected as the best-performing specification. The statistical significance of the differences in the mean factor scores and pesticide expenditure between the two identified groups was subsequently confirmed using an ANOVA test ($p < 0.01$), thereby validating the segmentation.

2.4. Fixed effects regression model

To isolate the causal impact of farm performance on pesticide expenditure, the analysis employed a fixed effects panel data regression model in log-linear form. This methodological choice was specifically adopted to mitigate the effect of unobserved heterogeneity, a pervasive issue inherent in farm-level data analysis [34]. The Hausman specification test [35] strongly rejected the null hypothesis that the individual effects are uncorrelated with the regressors ($\chi^2 = 312.44$; $p < 0.001$). Consequently, the fixed effects specification was preferred, as it yields consistent estimates when time-invariant unobserved heterogeneity is correlated with the explanatory variables.

The fixed effects model eliminates the effect of all omitted firm characteristics, ensuring that the estimated coefficients are not biased and reflect a purer causal relationship. The model uses cluster-robust standard errors to correct the potential autocorrelation within this term over time. By exploiting the variation over time of the key variables, the fixed effects model measures the within-firm causal effect: by how much the pesticide expenditure of that specific farm changes. The adopted model follows:

$$\ln(\text{Pesticide expenses}_{it}) = \alpha + \beta_1 \text{PC1}_{it} + \beta_2 \text{PC2}_{it} + \beta_3 \text{PC3}_{it} + \sum_{k=2}^K \delta_k (\text{Area}_i \times \text{Year}_t) + \sum_{m=2}^M \gamma_m (\text{UAA}_i \times \text{Year}_t) + \sum_{t=2}^T \lambda_t \text{Year}_t + u_i + \epsilon_{it}$$

The explanatory variables used in the fixed effects panel regression model are defined as follows: $\ln(\text{pesticide expenses}_{it})$ = the dependent variable, pesticide expenditure (transformed using the natural logarithm).

PC1_{it} = the principal component 1 factor score for firm i in year t .

PC2_{it} = the principal component 2 factor score for firm i in year t .

PC3_{it} = the principal component 3 factor score for firm i in year t .

Table 3

Eigenvalues and total variance explained by principal components (PCA).

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	8.902	59.349	59.349	8.902	59.349	59.349	7.070	47.131	47.131
2	1.664	11.096	70.445	1.664	11.096	70.445	3.347	22.315	69.446
3	1.274	8.492	78.937	1.274	8.492	78.937	1.424	9.490	78.937
4	0.907	6.044	84.980						
5	0.673	4.489	89.469						
6	0.608	4.052	93.521						
7	0.407	2.714	96.235						
8	0.333	2.221	98.456						
9	0.204	1.363	99.819						
10	0.018	0.118	99.936						
11	0.005	0.033	99.969						
12	0.003	0.022	99.992						
13	0.001	0.008	100.000						
14	0.000	0.000	100.000						
15	0.000	0.000	100.000						

Table 4
Rotated component matrix (factor loadings) and component interpretation.

	Component 1 (PC1) Economic- financial performance	Component 2 (PC2) Production Costs and EU support	Component 3 (PC3) Production intensification model
Total company revenue	0.843	0.509	0.119
Gross marketable production	0.850	0.458	0.130
European Union subsidies	0.072	0.347	-0.341
Fertilizer expenses	0.167	0.064	0.783
Mechanization expenses	0.037	0.172	0.768
Water, electricity and fuel expenses	0.281	0.756	0.105
Added value	0.913	0.375	0.062
Net company product	0.944	0.294	0.052
Salaries and social charges	0.211	0.761	0.038
Operating income	0.978	0.148	0.051
Net income	0.845	0.007	0.027
Variable costs	0.518	0.692	0.204
Fixed costs	0.184	0.829	0.052
Farm net value added	0.942	0.299	0.060
Gross operating margin	0.946	0.266	0.060

$\text{Area}_i \times \text{year}_t$ = the area-year interaction term. This term captures differentiated annual growth trends in pesticide expenditure across the geographical area.

$\text{UAA}_i \times \text{year}_t$ = the Utilised Agricultural Area (UAA)-year interaction term. This term captures differentiated annual growth trends in expenditure based on UAA.

Year_t = the time effect. This controls for temporal systemic macroeconomic shocks.

u_i = unobserved firm-specific fixed effect. This term captures all unobserved, time-invariant characteristics of firm i . The fixed effects estimation technique eliminates this source of bias.

ϵ_{it} = the idiosyncratic error term (residual). This represents the unexplained variation in expenditure for firm i in year t .

Since the dependent variable is in natural logarithms, the interpretation of the coefficients is in terms of elasticity and percentage changes. The fixed effects analysis was conducted on a balanced panel, ensuring that every farm was observed across all five years. This balanced structure is critical as it maximises the model's ability to isolate the within-firm temporal variation (within effect), which is the foundation for estimating a non-biased causal relationship unconfounded by time-invariant heterogeneity (u_i). The model's robustness was further strengthened by including dynamic interactions for the structural variables area and UAA, which, through interaction with the year, allow for the measurement of differentiated annual growth trends without the structural effect being eliminated by the fixed effects [34]. Finally, the use of cluster-robust standard errors corrects the autocorrelation of errors within each farm over time. This ensures a more rigorous analysis of expenditure dynamics, clearly distinguishing between the impact of internal decisions and macroeconomic fluctuations (the year effects) [36].

In summary, the methodology is designed to identify the latent structural dimensions of Italian wine farms, segment the sector according to farm typologies and pesticide expenditure, and estimate the within-farm effects of these dimensions on expenditure dynamics while accounting for farm size, geographical area, and temporal heterogeneity.

3. Results

3.1. *k*-means clustering

Cluster 1, labelled as the intensive production model, includes about 10% of the sample and is characterised by higher economic performance, greater production costs, and markedly stronger production intensification. Its average pesticide expenditure reaches 1,249.8 euro per hectare, more than three times the level observed in Cluster 2. By contrast, Cluster 2 represents the conventional model and shows slightly negative scores across the principal components, consistent with lower profitability, less intensive input use, and substantially lower pesticide expenditure (Table 5).

3.2. Fixed effects regression model

The fixed effects regression model, utilising cluster-robust standard errors to address potential heteroskedasticity and serial autocorrelation, proved to be statistically significant overall ($F(13, 686) = 11.95$; $p < 0.001$). The results highlight that all three structural principal components significantly influence firm pesticide expenditure. The strongest impact is unequivocally associated with production model intensification (PC3) (Coeff.=0.212; $p < 0.001$). The economic-financial performance component (PC1; Coeff.=0.108; $p = 0.002$) and the production costs/EU subsidies component (PC2; Coeff.=0.164; $p < 0.001$) also have significant positive effects on pesticide expenditure. Analysing the regional dynamics, the interaction terms reveal that several geographical areas experienced faster expenditure growth compared to the baseline region (South and Islands). Specifically, the Centre region demonstrated the largest additional annual growth trend (Coeff.=0.067; $p = 0.004$). Furthermore, the firm size analysis shows a significant relationship between smaller firms and expenditure growth: farms with an agricultural area of 5-15 ha and those with less than 5 ha exhibited significant additional annual expenditure growth (Coeff.=0.104 and 0.103, respectively) compared with the largest firms (> 40 ha, the omitted category). Finally, the fixed effects capture the influence of external shocks: compared to the baseline year (2019), general expenditure experienced a significant collapse in 2022 (Coeff.= -0.522; $p < 0.001$), followed by a rebound in 2023, underscoring a period of extreme macroeconomic volatility that affected the entire sector (Table 6).

The analysis of the predictive margins provides crucial insight into the expected level of pesticide expenditure for each geographical area-year combination. The results confirm that the predicted mean expenditure is statistically significant for all area-year combinations, as indicated by the consistently high z values and $P > |z|$ values of 0.000. More importantly, the margins illustrate the spatial and temporal polarisation of expenditure trends. Across all regions, a general decline in predicted expenditure is observed from 2021 to 2022, mirroring the macroeconomic shock identified by the year fixed effects, followed by a sharp rebound in 2023. Spatially, the Centre region maintains the highest

Table 5
K-means analysis results.

	Cluster 1 (n=355) Farms adhering to the intensive model	Cluster 2 (n=3085) Farms adhering to the conventional model
Pesticide Expenses	1249.8	357.9
REGR factor score 1	0.309	-0.036
REGR factor score 2	0.307	-0.035
REGR factor score 3	0.800	-0.092

All factors are significant according to the ANOVA results ($p < 0.01$).

Table 6

Fixed effects panel regression on pesticide expenditure with cluster-robust standard errors.

	Coefficient	Robust std. error	t	P> t	[95% Conf. Interval] Inf.	[95% Conf. Interval] Sup.
PC1	0.108	0.034	3.14	0.002	0.040	0.175
PC2	0.164	0.034	4.77	0.000	0.097	0.232
PC3	0.212	0.023	9.09	0.000	0.166	0.258
Geographical localization x year						
Center	0.067	0.023	2.88	0.004	0.021	0.113
Northeast	0.036	0.015	2.32	0.021	0.005	0.066
Northwest	0.006	0.021	0.30	0.764	-0.035	0.047
South and Islands		(omitted)				
Agricultural area x year						
< 5 ha	0.103	0.042	2.48	0.013	0.021	0.185
5-15 ha	0.104	0.041	2.52	0.012	0.023	0.184
15 - 40 ha	0.081	0.041	1.96	0.051	0.000	0.162
> 40 ha		(omitted)				
Temporal effects (Year)						
2020	-0.111	0.047	-2.35	0.019	-0.204	-0.018
2021	-0.281	0.089	-3.17	0.002	-0.456	-0.107
2022	-0.522	0.132	-3.96	0.000	-0.781	-0.263
2023	-0.489	0.175	-2.80	0.005	-0.833	-0.146
constant	5.679	0.044	129.55	0.000	5.593	5.765

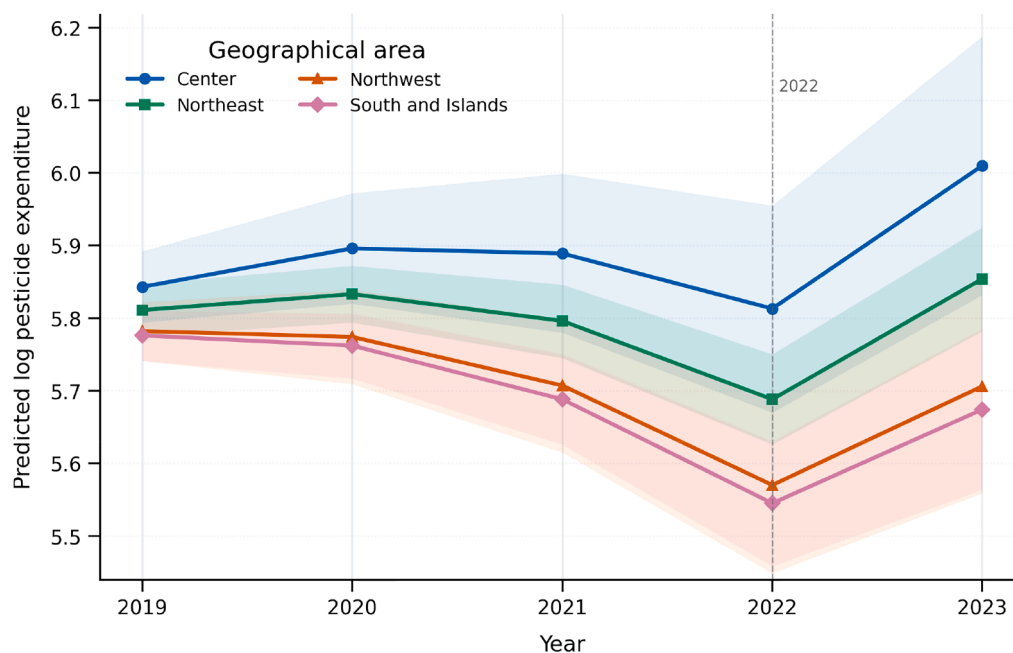
F(13.686) = 11.95 (Prob > F=0.0000). Sigma u=0.762; sigma e=0.411; rho=0.775.

predicted mean expenditure, while the South and Islands consistently exhibit the lowest mean expenditure, dropping to a minimum in 2022. The standard errors generally increase over time within each area, indicating greater uncertainty in the more recent estimates. Full details are reported in Table 7 annexed (Fig. 2).

The analysis of the predictive margins for each UAA class-year combination is highly statistically significant ($p < 0.001$). The key finding is the clear inverse relationship between firm size and expected expenditure level: the smallest categories (< 5 ha and 5-15 ha) maintain the highest predicted mean expenditures across the entire period, reaching high values in 2019 and 2020 and rebounding strongly in 2023 (e.g., 5.819 for 5-15 ha in 2023). Conversely, the largest firms (> 40 ha) consistently exhibit the lowest predicted expenditure, reaching a minimum of 5.245 in 2022. Temporally, all size classes display the same pattern observed in the regional analysis: a sharp decline in predicted

expenditure in 2022, corresponding to the macroeconomic shock, followed by a significant recovery in 2023. The predictions for the largest firms in recent years are subject to considerably greater uncertainty compared with smaller farms: the standard errors for the > 40 ha class increase dramatically over the period, from 0.041 in 2019 to 0.199 in 2023. Full details are reported in Table 8 annexed (Fig. 3).

Fig. 4 illustrates the temporal analysis of the predictive margins of pesticide expenditure, highlighting a period of relative stability between 2019 and 2021, with mean log expenditure values hovering around 5.80 (e.g., 5.798 in 2019 and 5.806 in 2020). A significant decline is sharply evident in 2022, where the predicted mean log expenditure dropped to 5.633. This decline strongly corresponds with the systemic macroeconomic volatility captured by the year fixed effects in the primary regression. Following this shock, 2023 exhibited a substantial and rapid rebound, with the mean log expenditure rising back to 5.785, nearly

**Fig. 2.** Predictive margins of pesticide expenditure for each specific combination of geographical area and year.

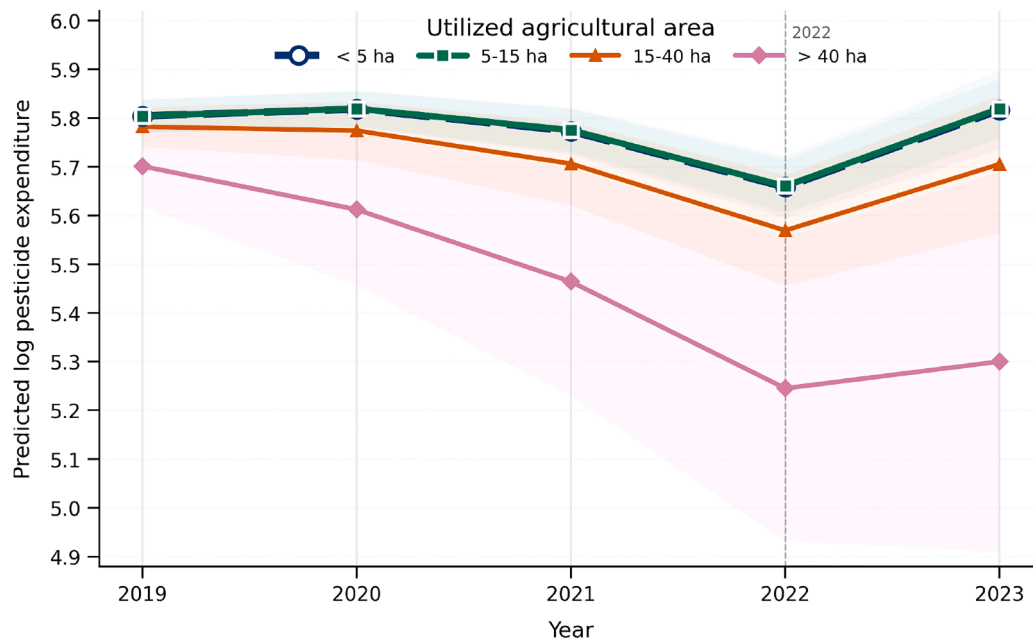


Fig. 3. Predictive margins of pesticide expenditure for each specific combination of UAA and year.

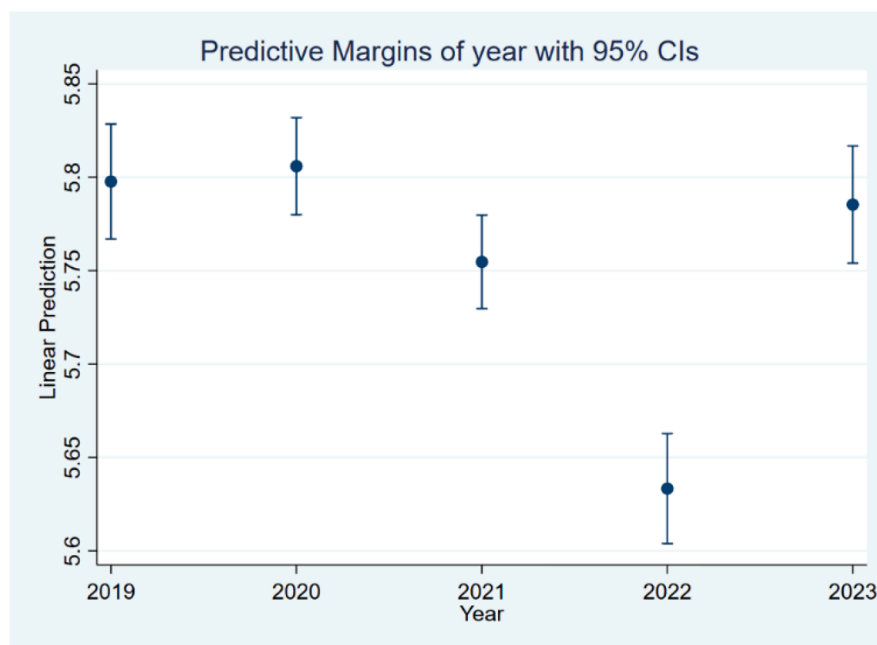


Fig. 4. Temporal analysis of the predictive margins of pesticide expenditure.

returning to the pre-shock levels of 2019. Full details are reported in Table 9 annexed.

4. Discussions & policy implication

This study addresses a key gap in the literature by providing a micro-level analysis of the drivers of pesticide expenditure in the Italian wine sector using a multi-stage methodology applied to FADN data. The discussion of the findings must therefore be read directly in light of the empirical evidence presented in the results section. The k-means analysis showed a clear structural polarisation between an intensive production model and a conventional model, while the fixed effects regression confirmed that pesticide expenditure is significantly shaped

by production intensification, economic-financial performance, production costs and EU support, farm size, geographical location, and year-specific shocks. These results indicate that policy design should explicitly account for three empirically identified dimensions: production intensification, farm size, and geographical location. These dimensions explain substantial differences in pesticide expenditure dynamics and therefore represent key criteria for designing more efficient and targeted intervention strategies.

First, the empirical evidence suggests that pesticide expenditure reflects the underlying business model rather than only short-term input choices. This interpretation is directly supported by the cluster analysis reported in Table 5: Cluster 1, representing around 10% of the sample, displays markedly higher scores for the production intensification

component and records pesticide expenditure of 1,249.8 euros per hectare, compared with 357.9 euros per hectare in Cluster 2. The fixed effects results in Table 6 reinforce this finding, since PC3, interpreted as the production intensification model, has the strongest coefficient among the three principal components (Coeff.=0.212; $p<0.001$). These results show that the highest pesticide expenditure is concentrated in farms whose structural profile combines more intensive input use and stronger economic performance. Future revisions of the CAP and the Green Deal should address the decoupling of agricultural profitability from intensive production models by refining eco-scheme mechanisms to more effectively reward de-intensification [37,38]. The evidence suggests that despite the rebranding of income support toward sustainability [39], pesticide input intensity remains closely connected to farm performance, creating a direct conflict between traditional profitability and the ecological transition [40]. This tension highlights the dual challenge of optimising economic outcomes while advancing socio-environmental goals [41,42].

Second, the results on farm size indicate that smaller farms require specific support because their expenditure dynamics suggest greater vulnerability to rising input dependence. This policy implication follows directly from the UAA-year interaction terms in Table 6, where farms below 5 ha and those between 5 and 15 ha show significant additional annual expenditure growth compared with the largest farms (>40 ha). The predictive margins by UAA class further confirm that the smallest size categories maintain the highest expected expenditure levels over the period and rebound strongly in 2023 after the 2022 decline. This is particularly relevant because many pesticide-reduction strategies increasingly rely on technological and managerial innovations that may be less accessible to small-scale producers. A growing body of literature shows that site-specific crop management, supported by remote sensing, decision support systems, the integration of big data, smart sensors, real-time monitoring, and variable-rate technologies, can reduce pesticide use or improve input efficiency [43–46]. Therefore, support measures should combine financial incentives with technical assistance primarily, though not exclusively, tailored to small-scale producers. For these farms, collective advisory schemes, technology-transfer programmes, cooperative access to precision tools, shared machinery arrangements, and locally adapted integrated pest management strategies may represent appropriate and feasible support options.

Third, the significant positive trend observed for the Central region indicates that territorial heterogeneity should be explicitly considered when designing pesticide-reduction policies. This implication is grounded in the fixed effects results, where the Centre shows the largest additional annual growth trend in pesticide expenditure relative to the South and Islands baseline (Coeff.=0.067; $p=0.004$), and in the predictive margins, which identify the Centre as the area with the highest expected expenditure levels. This pattern suggests that regional dynamics differ substantially across the Italian wine sector and may reflect differences in pedoclimatic conditions, production systems, disease pressure, and the types of grape variety produced across areas. Beyond environmental characteristics, quality certification schemes, such as Protected Designation of Origin (PDO) and Protected Geographical Indication (PGI), may also influence the observed outcomes [47], although their role was not explicitly assessed within the empirical framework adopted in this study. Because expenditure trajectories differ across areas, place-based interventions can better adapt support measures to local agronomic, environmental, and socio-economic conditions. This reinforces the relevance of evidence-based and place-based policy design, particularly in regions where expenditure trends reveal increasing dependence on chemical inputs. This territorial perspective is also relevant from a climate-policy standpoint. Where expenditure trends reveal increasing dependence on chemical inputs, pesticide-reduction strategies may contribute not only to local environmental protection but also to broader mitigation objectives, since agricultural pesticides are associated with greenhouse gas emissions [48–50]. Therefore, place-based pesticide-reduction policies in the wine

sector can also support international climate mitigation targets, particularly in territories where expenditure dynamics indicate a stronger structural reliance on chemical inputs [51].

Furthermore, the temporal effects reported in Table 6 and the predictive margins show that pesticide expenditure is exposed to systemic shocks. The significant contraction observed in 2022, followed by a partial rebound in 2023, indicates that expenditure dynamics are influenced not only by farm structural characteristics but also by broader economic conditions. In policy terms, this means that pesticide-reduction strategies should be accompanied by risk-management instruments capable of maintaining sustainability objectives during periods of market instability. The 2022 decline should not be interpreted as evidence of a stable structural reduction in pesticide dependence, since the subsequent rebound suggests that farms may return to previous expenditure levels when economic conditions normalise. This reinforces the need for measures that enhance farmers' environmental awareness and strengthen the supervision of agricultural inputs [52].

Moreover, pesticide-related knowledge moderates behavioural mechanisms, reinforcing the link between attitudes, perceived behavioural control, and the adoption of safer pesticide practices [53]. Aubert and Enjolras [54] found that first-pillar subsidies may increase pesticide expenditures and cultivated areas, whereas second-pillar payments are associated with lower pesticide expenditure intensity. This suggests that policy design matters: support schemes aimed mainly at income stabilisation or farm expansion may indirectly reinforce input-intensive strategies, while targeted rural development and agri-environmental measures can better support pesticide reduction.

A key caveat of this study is that pesticide expenditure should not be treated as a direct ecological indicator, since pesticide costs, quantities applied and toxicity-based measures may capture only partially overlapping dimensions of pesticide-related pressure. Therefore, the present results should be interpreted as evidence on the economic and structural drivers of pesticide-related expenditure, rather than as a direct assessment of pesticide use intensity or environmental risk [55].

5. Conclusion

This study provides direct answers to the three research questions formulated in the Introduction. About RQ1, the PCA identifies three latent structural dimensions characterising Italian wine farms: economic-financial performance, production costs and EU support, and the production intensification model. These dimensions show that pesticide expenditure is embedded in broader farm structures rather than being an isolated input decision.

Concerning RQ2, the fixed effects regression shows that these structural dimensions significantly influence pesticide expenditure over time. The production intensification model emerges as the strongest driver, followed by production costs/EU support and economic-financial performance. The k-means analysis further confirms that a relatively small intensive cluster records substantially higher pesticide expenditure than the conventional cluster, indicating that expenditure patterns are strongly associated with distinct production models.

Concerning RQ3, the results demonstrate that farm size and geographical location moderate pesticide expenditure dynamics. Smaller farms, particularly those below 15 ha, show stronger annual expenditure growth than larger farms, while the Centre displays the highest additional territorial growth trend and the highest expected expenditure levels in the predictive margins. These findings confirm that pesticide-reduction policies should not be uniform but differentiated according to production intensity, farm size and territorial context. Intensive farms require incentives for de-intensification and input-efficiency improvements; smaller farms need accessible advisory services, cooperative technological solutions and financial support; and territories such as Central Italy require place-based strategies adapted to local expenditure trajectories. Overall, the transition toward a more sustainable, resilient and responsible Italian wine sector will depend on

policy instruments that reward lower-impact production models while preserving farm income and competitiveness.

Some limitations of this study should be acknowledged. First, pesticide expenditure should be interpreted as an economic and accounting indicator of the financial burden associated with crop protection, rather than as a direct measure of pesticide quantities applied, toxicity levels, pesticide-use intensity, or environmental risk. Second, the analysis relies on monetary variables expressed in nominal terms, as these were not deflated over the study period. Consequently, changes in pesticide expenditure should be interpreted as variations in nominal farm-level spending rather than as direct evidence of changes in real input use or price-adjusted costs.

This study identifies several priorities for future research. First, further work should investigate the behavioural and managerial factors underlying the intensive/high-performance cluster to clarify whether its higher use of inputs reflects structural constraints, strategic choices, or differences in technical and organisational capacity. Second, future analyses should quantify the externalised environmental costs associated with high-input production models in the Italian wine sector. Third, future research should integrate information on climatic variability,

spatial conditions, actual pesticide-use intensity, pesticide toxicity profiles, and the economic costs of transitioning toward lower-input systems.

Ultimately, achieving the Green Deal objectives requires moving beyond uniform pesticide-reduction targets towards differentiated policy instruments that recognise the structural diversity of European wine farms.

CRediT authorship contribution statement

Nicola Casolani: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Federica DeMaria:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Annex A

Table 7

Predictive margins of pesticide expenditure for each specific combination of geographical area and year.

Area	Year	Margin	Std. Err.	z	P> z	[95% Conf. Interval] Inf.	[95% Conf. Interval] Sup.
Center	2019	5.843	0.025	233.580	0.000	5.794	5.892
Center	2020	5.896	0.039	152.290	0.000	5.820	5.972
Center	2021	5.889	0.056	105.230	0.000	5.780	5.999
Center	2022	5.813	0.073	79.890	0.000	5.670	5.955
Center	2023	6.010	0.091	66.240	0.000	5.832	6.188
Northeast	2019	5.811	0.018	316.770	0.000	5.775	5.847
Northeast	2020	5.833	0.020	291.250	0.000	5.794	5.872
Northeast	2021	5.796	0.026	225.740	0.000	5.745	5.846
Northeast	2022	5.688	0.032	178.920	0.000	5.626	5.750
Northeast	2023	5.854	0.036	160.700	0.000	5.782	5.925
Northwest	2019	5.782	0.021	278.990	0.000	5.741	5.822
Northwest	2020	5.774	0.033	173.810	0.000	5.709	5.839
Northwest	2021	5.707	0.047	121.930	0.000	5.615	5.799
Northwest	2022	5.570	0.062	90.150	0.000	5.449	5.691
Northwest	2023	5.706	0.075	76.310	0.000	5.559	5.852
South and Islands	2019	5.776	0.017	332.320	0.000	5.741	5.810
South and Islands	2020	5.762	0.023	251.390	0.000	5.717	5.806
South and Islands	2021	5.688	0.032	180.540	0.000	5.626	5.750
South and Islands	2022	5.545	0.043	127.490	0.000	5.459	5.630
South and Islands	2023	5.674	0.056	100.670	0.000	5.564	5.785

Table 8

Predictive margins of pesticide expenditure for each specific combination of UAA and year.

Utilized agricultural area (UAA)	Year	Margin	Std. Err.	z	P> z	[95% Conf. Interval] Inf.	[95% Conf. Interval] Sup.
15-40 ha	2019	5.782	0.021	281.300	0.000	5.741	5.822
15-40 ha	2020	5.774	0.030	190.560	0.000	5.714	5.833
15-40 ha	2021	5.706	0.043	131.760	0.000	5.621	5.791
15-40 ha	2022	5.569	0.058	96.810	0.000	5.456	5.682
15-40 ha	2023	5.705	0.072	79.700	0.000	5.564	5.845
5-15 ha	2019	5.804	0.017	346.070	0.000	5.772	5.837
5-15 ha	2020	5.819	0.019	311.250	0.000	5.783	5.856
5-15 ha	2021	5.775	0.022	259.770	0.000	5.731	5.818
5-15 ha	2022	5.660	0.027	206.520	0.000	5.606	5.714
5-15 ha	2023	5.819	0.031	188.950	0.000	5.759	5.879
< 5 ha	2019	5.804	0.018	330.120	0.000	5.769	5.838
< 5 ha	2020	5.818	0.019	309.520	0.000	5.781	5.855
< 5 ha	2021	5.773	0.024	236.040	0.000	5.725	5.821

(continued on next page)

Table 8 (continued)

Utilized agricultural area (UAA)	Year	Margin	Std. Err.	z	P> z	[95% Conf. Interval] Inf.	[95% Conf. Interval] Sup.
< 5 ha	2022	5.658	0.032	175.320	0.000	5.595	5.721
< 5 ha	2023	5.816	0.041	142.870	0.000	5.736	5.896
> 40 ha	2019	5.701	0.041	137.500	0.000	5.619	5.782
> 40 ha	2020	5.612	0.079	70.890	0.000	5.457	5.767
> 40 ha	2021	5.464	0.119	46.040	0.000	5.231	5.696
> 40 ha	2022	5.245	0.159	33.040	0.000	4.934	5.556
> 40 ha	2023	5.300	0.199	26.700	0.000	4.911	5.689

Table 9
Temporal predictive margins of pesticide expenditure.

Year	Margin	Std. Err.	z	P> z	[95% Conf. Interval] Inf.	[95% Conf. Interval] Sup.
2019	5.798	0.016	369.24	0.000	5.767	5.829
2020	5.806	0.013	437.53	0.000	5.780	5.832
2021	5.755	0.013	450.86	0.000	5.730	5.780
2022	5.633	0.015	375.01	0.000	5.604	5.663
2023	5.785	0.016	361.14	0.000	5.754	5.817

Data availability

Data will be made available on request.

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