European Review of Agricultural Economics, Vol **0** (**0**) (2026) pp. 1–55
https://doi.org/10.1093/erae/jbag010

Advance Access Publication 17 June 2026

The relationship between pesticides and risk in apple production

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Received 29 July 2024; Final version accepted 5 May 2026

Abstract

We examine how pesticide expenditure relates to the probability distribution of yield and revenue per hectare in apple production in northern Italy. Using a flexible moment-based approach, we find that pesticide expenditure is negatively associated with downside risk in yield and revenue, whereas late frosts are positively associated with downside risk in yield. Sensitivity analyses show that mean-equation estimates are robust to unobserved confounders, while negative semi-variance models are less robust overall. Only the pesticide–expected outcome relationship appears plausibly causal. Therefore, conclusions about pesticides as risk-increasing or risk-decreasing inputs should be made with caution.

Keywords: risk; weather; yield variability; revenue variability; apple

JEL classification: Q12, Q18

1. Introduction

Crop pests cause significant yield losses and quality degradation in agriculture. This highlights the critical importance of selecting and enforcing effective pest management strategies (Savary *et al.*, 2019; Möhring *et al.*, 2020a; Finger and Möhring, 2025). To date, modern agricultural systems have mostly relied on the use of synthetic pesticides to control crop pests (Sharma *et al.*, 2019). However, their use has significant drawbacks: they can harm the environment (Dias *et al.*, 2023), contribute to biodiversity loss (Wan *et al.*, 2025) and pose risks to human health (Kim *et al.*, 2017; Athukorala *et al.*, 2023). In light of these challenges, the European Union (EU) has long prioritized the reduction of pesticide (and fertilizer) use on its environmental agenda.

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This issue is open to political debate, and while targets and objectives for a more sustainable agri-food system transition have been set, they have largely remained abstract, with the question of how to actually reach them still unclear (Finger *et al.*, 2024; Finger and Möhring, 2025). Achieving a long-term transformation, however, requires a systemic change of the entire agri-food system (Brunelle *et al.*, 2024), on which farmer's choices of pesticide use play an important role in policy effectiveness.

Farmers' decisions regarding pesticide use are shaped by their risk perceptions, risk preferences and the effect of pesticides on agricultural risk (Gong *et al.*, 2016; Chèze *et al.*, 2020; Möhring *et al.*, 2020b; Bontemps *et al.*, 2021; Brunelle *et al.*, 2024; Finger and Möhring, 2025). In this respect, the correlation between pesticides and agricultural production risk is still unclear, as literature offers conflicting evidence. Some studies find higher pesticide application being correlated with a higher level of risk (Serra *et al.*, 2006, 2008), others with a lower level of risk (Koundouri *et al.*, 2009; Antle, 2010; Gardebroek *et al.*, 2010), and a few studies find no correlation (Hurd, 1994). The reason for the heterogeneity of these results lies in the different agricultural products, different countries and different indicators used to measure pesticide use in the different studies (Möhring *et al.*, 2020b). Understanding whether pesticides increase or reduce risk helps better delineate the context in which farmers make decisions and inform the design of more effective policies targeting pesticide reduction. Since the average farmer tends to be risk-averse (Koundouri *et al.*, 2009; Mulungu *et al.*, 2024), any change in agricultural risk is expected to prompt changes in decision-making overall. For instance, if pesticides are risk-reducing, any constraint on application rates could lead to compensatory behaviour, such as using more toxic active ingredients or implementing other risk management strategies, which policymakers should anticipate to ensuring more effective policymaking.

In this paper, we explore the relationship between pesticide use and expected yield and per-hectare revenue, as well as the role that the application of pesticides plays on curbing or increasing the corresponding overall variance and negative semi-variance, which identifies downside risk in agricultural production. We use an unbalanced sample of 303 apple farms from Northern Italy observed over the period 2015–2020. The apple sector is economically significant in the EU. Apple orchards account for more than one-third of all EU fruit plantations (Eurostat, 2019), and Italy alone has about 12 per cent of the total EU apple-growing area (Eurostat, 2024). However, apple production relies heavily on pesticide applications, with annual treatments sometimes exceeding 30 (Simon *et al.*, 2011; Suchail *et al.*, 2018; Zaller *et al.*, 2023). These treatments are used not only to secure yields, but also to meet cosmetic standards (Zachmann *et al.*, 2024a). Pesticide use is especially high for the 'Golden Delicious' variety, one of the most cultivated in Northern Italy (Simon *et al.*, 2011).

We employ a moment-based approach (Antle, 1983, 2010) to investigate the correlation between pesticide expenditure and the first (mean) and the second (variance) moments of the agricultural output probability distribution in the apple sector (e.g. Di Falco and Chavas, 2006, 2009; Huang *et al.*, 2015; Finger *et al.*, 2018; Bozzola and Smale, 2020; Biagini and Severini, 2022).

Identifying the causal effect of pesticide use on the moments of agricultural output probability distribution poses several empirical challenges, largely due to the confounding effect of unobservable factors tied to both pest pressure and the stochasticity of crop growth (Horowitz and Lichtenberg, 1994). For this reason, our empirical approach implements a set of strategies to provide credible estimates. First, since pest pressure is unobservable yet strongly correlated with farm-level weather conditions (Deutsch *et al.*, 2018) and given that the increase in climate variability has amplified the downside risk (Kim and Chavas, 2003; Kim *et al.*, 2014), we incorporate synthetic weather indicators into the model. Meteorological data are obtained from the ERA5 global reanalysis dataset (Hersbach *et al.*, 2020) and interpolated to the geographical centroids of individual farms in the Farm Accountancy Data Network (FADN) using a spatial matching algorithm. Second, we include year and farm-level fixed-effects in our model to absorb time-invariant farm-level management practices that influence both pesticide use and baseline pest pressure as well as crop yield. Third, we assess robustness to unobserved confounding using an array of sensitivity analyses. Finally, we assess the stability of our estimates by running many robustness checks.

We contribute to the literature in several ways. First, our study provides an empirical application of the theoretical literature on the farmer decision-making under uncertainty (Hardaker *et al.*, 2004; Lien *et al.*, 2022). While we acknowledge that the association between pesticide use on apples has already been studied in a different geographical context (Babcock *et al.*, 1992), we extend previous research by also focusing on the variability of yield and revenue. In particular, the focus on the negative semi-variance allows us to emphasize downside risk, which is particularly relevant in agriculture, where farmers tend to be more concerned with losses below the mean than with above-average outcomes (Koundouri *et al.*, 2009; Mulungu *et al.*, 2024). Second, to the best of our knowledge, this is the first study in which hourly satellite meteorological data are spatially interpolated at the location of individual farms included in the FADN in order to control for the farm-level weather influence on crop output. This contributes to the ongoing debate and growing body of knowledge on the use of satellite data in agricultural economics research (Wuepper *et al.*, 2025). Third, we apply four sensitivity analyses to both the expected output model and the variance model, extending the sensitivity analysis toolkit for this class of empirical models which, so far, has been applied to the expected output model only.

The results of our analysis indicate that pesticide use is positively associated with the expected yield and revenue per hectare, while it is negatively associated with the negative semi-variance of both outcomes. Sensitivity analyses demonstrate that the results of the expected value equations are moderately robust to unobserved confounders, with the yield model showing lower sensitivity than the revenue-per-hectare model. On other hand, negative semi-variance models tend to be much less robust to unobserved confounders, with results concerning revenue-per-hectare being once again weaker than those for yield. For this reason, we claim that only the estimated association between pesticide expenditure and the first moment of the two outcomes can be expected to reasonably approximate the unknown causal relationship. Consequently, any firm conclusion on pesticides as risk-increasing or risk-decreasing input should be made with caution. Rather, we simply acknowledge that apple farmers applying more pesticides tend to experience a lower downside risk. This correlation could nevertheless represent helpful (preliminary) information for defining any policy related to pesticide use in apple farming that simultaneously accounts for either potential side effects (i.e. if pesticides cause a decrease in the downside risk, a policy that constrains the pesticide use would increase the agricultural risk) and the heterogeneous impact on farmers (i.e. if farmers who experience a lower level of risk uses more pesticides, those farmers will be more affected by a policy constraining pesticide use).

2. Methodology

2.1 Conceptual framework

Following standard production theory under risk, we consider a production process in which a farmer maximizes her expected utility of wealth, W, by choosing an input vector $\boldsymbol{x}$:

$$\max_{\boldsymbol{x}} E\left[U\left(W\right)\right] = \max_{\boldsymbol{x}}\ E\left[U\left(W_0 + pq\left(\boldsymbol{x}, \boldsymbol{s}\right) - \boldsymbol{wx}\right)\right], \tag{1}$$

where W_0 indicates fixed (i.e. non-stochastic) initial wealth, $q(\boldsymbol{x}, \boldsymbol{s})$ is a stochastic production function, $\boldsymbol{s}$ is a vector of random uncontrolled factors affecting q, p is the random output price and $\boldsymbol{w}$ is a vector of non-random input prices.

In general, expected utility can be modelled as a function of k moments of the wealth distribution. However, as discussed in Serra *et al.* (2006), we assume that only the first two moments matter, i.e. that farmers optimal decision-making involves ranking different alternatives through a utility function defined over the mean and the variance of random wealth:

$$\max_{\boldsymbol{x}} E\left[U\left(W\right)\right] = \max_{\boldsymbol{x}}\ V\left[\bar{W}, \sigma_W^2\right], \tag{2}$$

where the specification of $\bar{W}$ and σ_W^2 depends on the assumptions concerning the structure of the stochastic production function and the relationship between price and output variability (see Serra *et al.*, 2006 for details).

2.2 Econometric framework

Given the problem in (2) and adopting the moment-based approach as originally proposed by Antle (1983), our research question (i.e. the relationship between pesticide use and risk in apple production) can be addressed by parameterizing the two moments of the wealth distribution. Unfortunately, due to data limitations, a proper measure of farmers' wealth is usually not available, since farm-level surveys tend to exclude the off-farm sources of income/wealth (Moro and Sckokai, 2013). Thus, since random wealth is essentially influenced by the variability of farm revenue, a common choice in the literature is that of parameterizing the first two moments of farm revenue (Finger *et al.*, 2018), since variable costs are typically considered as non-random. In addition, another relevant stream of literature focuses on the first two moments of yield, in order to disentangle the contribution of yield uncertainty to revenue variability (Di Falco and Chavas, 2006; Di Falco and Chavas, 2009; Huang *et al.*, 2015). Since in apple production yield volatility is particularly strong (Kviklys and Martinussen, 2025), in our analysis we explore the distributions of both outcomes: crop yield and crop revenue. This is particularly relevant to our research question because yield captures the direct relationship between pesticide use and quantity produced, whereas revenue includes the indirect effect of pesticide use on apple prices. Different levels of pesticide application or quality, for example, may affect the quality and aesthetic of the apples (Zachmann *et al.*, 2024a), which can influence the price received by the farmer.

Since our focus is on input use, for simplicity we define the variance of the outcome distribution as $E[y(\boldsymbol{x}, \boldsymbol{s}) - E(y(\boldsymbol{x}, \boldsymbol{s})]^2$, where y is the outcome of interest (yield or revenue) and $\boldsymbol{s}$ is a vector of all other factors different from inputs which affect the outcome y. However, limiting the analysis to the first two moments of the yield (revenue) distribution does not fully capture all the components of the farmer utility. Indeed, crop yield and revenue are often subject to adverse events, either due to weather conditions or pest infestations, which affect the lower tail of the yield and revenue distribution (Huang *et al.*, 2015; Schmitt *et al.*, 2022). Moreover, farmers are usually more concerned about realization in the lower tail of the distribution than in the upper tail, i.e. downside risk (Koundouri *et al.*, 2009; Mulungu *et al.*, 2024), as their decrease in utility due to uncertainty under the expected value is higher than the decrease in utility due to uncertainty above the expected value. To account for downside risk exposure either the moments higher than two (Antle, 1983; Huang *et al.*, 2015) or the negative semi-variance should be considered (Antle, 2010; Finger *et al.*, 2018). Since in our study we assume that only two moments matter, we consider the negative semi-variance, defined as the variance below a specific benchmark, which is usually set equal to the expected value of the random outcome variable, that is $E[y(\boldsymbol{x}, \boldsymbol{s}) - E(y(\boldsymbol{x}, \boldsymbol{s})]^2$ when $y(\boldsymbol{x}, \boldsymbol{s}) < E[y(\boldsymbol{x}, \boldsymbol{s})]$.[1] Clearly, the utility of a downside risk averse farmer increases with an increase in expected revenue and with a decrease in negative semi-variance.

1 Finger *et al.* (2018) and Kim *et al.* (2014) outline that the estimation of moments higher than two with panel data often carries estimation challenges and lead to non-significant parameters. We tried to consider also the skewness of the yield and revenue distribution and, indeed, we found no significant results. We, thus, prefer to focus on the negative semi-variance and report the related results.

The moment-based approach originally proposed by Antle (1983) postulates that each moment of the probability distribution of the outcome depends on a distinct parameter vector. This flexible approach prevents cross-equation restrictions between moments, which would arise by imposing a specific structure to the stochastic production function. Thus, we have

$$y_i = \alpha_1 + h_y(\boldsymbol{x}_i; \boldsymbol{\beta}_1) + m_y(\boldsymbol{s}_i; \boldsymbol{\gamma}_1) + v_i, \tag{3}$$

where, y_i is crop yield or revenue per hectare realized in farm i, $\boldsymbol{x_i}$ is a L-sized vector of inputs, $\boldsymbol{s_i}$ is Q-sized vector of other control variables potentially affecting production, α_1 is an intercept term, while $\boldsymbol{\beta}_1$and $\boldsymbol{\gamma}_1$ are the coefficient vectors of the real-valued functions h_y and m_y in the conditional expectation (first moment) equation. Finally, v_i indicates a random error term capturing all components affecting the farm output but not observed by the researcher and satisfying $E(v_i) = 0$. From equation (3), we have that the first moment of the crop yield or revenue distribution is $\mu_1 = E(y_i) = \alpha_1 + h_y(\boldsymbol{x}_i; \boldsymbol{\beta}_1) + m_y(\boldsymbol{s}_i; \boldsymbol{\gamma}_1)$. Moreover, we can also parametrize the variance of the outcome distribution as follows:

$$v_i^2 = \alpha_2 + h_v(\boldsymbol{x}_i; \boldsymbol{\beta}_2) + m_v(\boldsymbol{s}_i; \boldsymbol{\gamma}_2) + \rho_i, \tag{4}$$

where, similarly to the mean value equation, α_2 is the intercept of the second moment of the yield or revenue distribution, the vectors $\boldsymbol{\beta}_2$ and $\boldsymbol{\gamma}_2$ contain the coefficients of the real-valued functions h_v and m_v in the second moment of the distribution, respectively, while ρ_i is the error term of the variance equation. The equation for the negative semi-variance is the same as Equation (3) but apply only to those observations where $v_i < 0$.

Equation (3) implies that error term of Equation (2), v_i, is heteroscedastic because its variance is by construction not constant across observations. To deal with this heteroscedasticity issue, we report heteroscedastic-robust standard errors of parameter estimates in the expectation equation (Antle, 1983).

2.3 Identification strategy

Although the use of two-way fixed effects allows us to control for unobservables that are constant within the same farm (farm effect) or in the same year across farms (time effect), we still face a potential endogeneity problem in the expected output model and in the variance model due to omitted variable bias (OVB) arising from unobservable factors that vary both over time and across farms such as farmers' risk perceptions, preferences and access to extension services as well as pest pressure and stochasticity of crop growth (Horowitz and Lichtenberg, 1994; Wuepper *et al.*, 2021; Finger, 2023). These factors, indeed, can influence both farmers' economic outcomes and their decisions about pesticide use, raising concerns about endogeneity. For example, higher pest pressure reduces expected yield and revenue and raises their variability, while at the same time heightening perceived risk and affecting pesticide use. If pesticides are perceived as risk-reducing input, their use under an increasing pest pressure is likely to raise and this may potentially result in overuse and lower marginal pesticide productivity (Liu and Huang, 2013; Gong *et al.*, 2016).

As these identification challenges are typically hard to address, our empirical approach implements several falsification strategies to provide credible correlation between pesticide use and crop output. Previous empirical studies that used moment-based estimators often addressed OVB with an instrumental variables (IV) strategy. These studies typically exploited weather shocks or lagged covariates as instruments (Di Falco and Chavas, 2009; Di Falco *et al.*, 2014; Finger *et al.*, 2018; Bozzola and Smale, 2020). However, the validity of these instruments has been questioned, particularly due to potential violations of the exclusion restriction (Bellemare *et al.*, 2017; Mellon, 2021). In line with these concerns and following the caution of Henningsen *et al.* (2024) against 'forced' causal identification when instruments are weak or the exclusion restriction is questionable, we refrain from using IVs and report non-causal estimates. To this extent, we strive to reinforce our identification strategy by including synthetic weather indicators and probing the consistency of the resulting estimates via multiple sensitivity analyses. Since pest pressure is unobservable yet strongly correlated with farm-level weather conditions (Deutsch *et al.*, 2018), and since increasing climate variability has raised the probability of adverse events, thereby amplifying downside risk (Kim and Chavas, 2003; Kim *et al.*, 2014), we incorporate synthetic weather indicators into the model (i.e. into the $\boldsymbol{s}_{it}$ vector).

Meteorological data are obtained from the ERA5 global reanalysis dataset (Hersbach *et al.*, 2020) and interpolated to the geographical centroids of individual farms in the FADN using a spatial matching algorithm. Not only does high frequency/spatial resolution help characterizing precise weather events in the proximity of the sampled farms, but it also allows to construct more accurate indicators for the meteorological phenomena of interest. To this end, our paper also presents a novel method for calculating growing degree days (GDD) that improves on the widely adopted approach discussed in Schlenker and Roberts (2009) and D'Agostino and Schlenker (2016) (see Section 3.1.1). We also run a set of sensitivity analyses to test the extent to which our findings are robust to unobserved heterogeneity and whether they can be claimed to approximate a causal effect. In particular, we first employ the sensitivity analysis proposed by Cinelli and Hazlett (2020) thereby obtaining robustness values (RV) that indicate how strongly an unobserved confounder must be correlated with both the treatment and the outcome to drive the estimated coefficient to zero (for previous applications, see Balaine *et al.*, 2023; Johnen and Mußhoff, 2023; Johnen *et al.*, 2023; Zachmann *et al.*, 2024b; de Soysa, 2025). Second, we implement the approach discussed in Stetter *et al.* (2022) and Coderoni *et al.* (2024), where the stability of treatment effect estimates in the presence of OVB is probed by re-estimating models (3) and (4) after including a synthetically generated confounder in the control variables set. Third, we apply Oster coefficient-stability test (2019). Fourth, we conduct both a treatment and an outcome placebo test following the approaches discussed in Eggers *et al.*

(2024). All these sensitivity tests and the related results are discussed in detail in Section 4.4.

2.4 Empirical model

The empirical model for the mean function consists of a quadratic specification where we set:

$$h_y\left(\boldsymbol{x}_{it};\boldsymbol{\beta}_1\right)=\sum_{l=1}^{L}\beta_{1l}x_{lit}+0.5\sum_{l=1}^{L}\sum_{n=1}^{L}\beta_{1ln}x_{lit}x_{nit}$$

$$m_y\left(\boldsymbol{s}_{it};\boldsymbol{\gamma}_1\right)=\sum_{q=1}^{Q}\gamma_{1\mathrm{q}}s_{qit}+\theta_i+\tau_t$$

such that:

$$y_{it}=\alpha_1+\sum_{l=1}^{L}\beta_{1l}x_{lit}+0.5\sum_{l=1}^{L}\sum_{n=1}^{L}\beta_{1ln}x_{lit}x_{nit}+\sum_{q=1}^{Q}\gamma_{1\mathrm{q}}s_{qit}+\theta_i+\tau_t+v_{it}, \quad (5)$$

where y_{it} indicates the apple yield in the yield model and the per-hectare apple revenue in the revenue model, while the subscripts l and n indicate inputs, such that x_{lit} represents how much input l farm i used in year t, when the farm is observed in that year. θ_i and τ_t are the farm and the time fixed effects, respectively.[2] On the other hand, in line with the literature on the moment-based approach we chose a simpler functional form for the variance and negative-semi-variance equations, where both $h_v(\boldsymbol{x}_{it};\boldsymbol{\beta}_2)$ and $m_v(\boldsymbol{s}_{it};\boldsymbol{\gamma}_2)$ are linear-in-coefficients.

The inputs included in our model are the ones in line with standard agricultural production economics (Antle and Chrisman, 1990; Di Falco and Chavas, 2009): per-hectare pesticide expenditure on apple area, per-hectare fertilizer use on apple area, measured in quantity terms and labour, measured by the number of yearly working hours per hectare.[3] In our analysis, we use pesticide expenditure as a proxy for pesticide use (Varacca *et al.*, 2023). This choice is primarily driven by the limitations of the Italian FADN data. Specifically, the pesticide quantity data in the Italian FADN lack a standardized unit of measurement: in some cases, quantities are reported as the number of packages—

2 As a robustness check, we compared the AIC and BIC of the linear quadratic form with those of the trans- log and linear-log forms. The results can be found in Appendix A, Table A1.

3 While there is agreement on the classification of inputs such as fertilizer as productivity-enhancing, the classification of pesticides is more contentious. Indeed, a broad stream of literature (e.g. Horowitz and Lichtenberg, 1994; Saha *et al.*, 1997; Lansink and Carpentier, 2001; Singbo *et al.*, 2015; Böcker *et al.*, 2018; Möhring *et al.*, 2020a), building on Lichtenberg and Zilberman (1986), adopts a production function framework that allows for a distinction between productive inputs, which increase potential output, and damage abatement inputs, which reduce the distance between potential and actual output. Within this framework, pesticides are treated as damage-abating inputs rather than productive inputs, based on the idea that they do not directly increase crop yields but instead reduce the negative impact of pests (Singbo *et al.*, 2015). However, in our work we align with another relevant strain of literature (Di Falco and Chavas, 2006; Koundouri *et al.*, 2009; Antle, 2010; Kim *et al.*, 2014; Huang *et al.*, 2015; Wang *et al.*, 2018) which does not make this distinction and instead treats pesticides as productive inputs.

whose sizes vary—while in others they are expressed in weight. This inconsistency prevents the development of a consistent and comparable measure of pesticide use across farms, rendering the quantity variable unsuitable for model estimation. In this respect, we acknowledge that relying on expenditure data does not allow us to distinguish spending variations due to higher/lower pesticide purchases from changes in pesticides' type and quality. To mitigate potential bias from quality-related variation, we restrict our sample to a relatively homogeneous group of farms. In particular, we focus on farms located in northern Italy that adopt similar production practices, and we further enhance comparability by excluding both organic and non-irrigated farms. This should ensure that pesticide quality is similar across farms in our sample and that pesticide expenditure is a scaled proxy for pesticide quantity. Nevertheless, had pesticide use been available as a homogeneous quantity measure, it would be an imperfect measure, as pesticides are highly heterogeneous in terms of the active ingredients they contain (Möhring *et al.*, 2019). The ideal scenario would involve having detailed information on the quantity of each active ingredient in the pesticides applied by individual apple farms. However, under the current EU regulations, Member States are only required to publish data on pesticide sales by group, rather than by active ingredient for each specific pesticide (Annex II of Regulation (EC) No 1185/2009). This makes such detailed information difficult—if not impossible—to obtain when relying on secondary data. Our input set does not include land because apple trees are perennial crops, so in most farms land allocation is approximately fixed throughout the period considered in our analysis.

As discussed in the previous Section, the control variable vector $\boldsymbol{s}_{it}$ consist of weather indicators that may potentially affect apple production and, we assume, correlate with the unobserved confounders. These variables are taken from the agronomic literature, and their values are defined at the farm level by interpolating grid-level data obtained from satellite information as detailed in Section 3.1.1.

Given the linear quadratic functional form of the first-moment equation, we ease the interpretation of the estimated model coefficients by computing the yield and revenue elasticities with respect to the input variables:

$$E_{x_l} = \frac{dy\,(x,s)}{dx_l}\frac{\bar{x}_l}{\bar{y}}, \tag{6}$$

where, $\frac{dy(x,s)}{dx_l}$ is the derivative of the crop yield (revenue) with respect to the input l. All elasticities are computed at the sample mean.

3. Data

3.1 Weather data and weather synthetic indicators construction

We collected weather data from the Copernicus Climate Change Service (C3S) API through the ERA 5 global reanalysis dataset (Hersbach *et al.*, 2020). The latter features detailed records regarding the global atmosphere, land surface and ocean waves from 1950 onwards and consists of hourly observations defined on a fine 0.1×0.1 degrees grid. Specifically, our interrogation targeted temperature[4] and total precipitation[5] data, which we either directly employed to calculate GDDs and characterize late frosts or aggregated at the daily level to identify heat waves and summer rainfalls. After constructing these artificial covariates, we integrated meteorological and accounting information through a spatial matching algorithm. This procedure involves extracting the four closest grid observations to each farm centroid in the FADN, weighting them by their inverse distance, and calculating the corresponding weighted average to produce farm-level indicators for the above mentioned whether events (see Fig. 1).

The choice of the weather variables to include was based on the agronomic literature and on expert consultations and it consists of information on late frosts, heat waves and precipitation. These weather variables are the ones that most affect apple production. In the following subsections, we describe each variable and the relevant literature they are based on.

3.1.1 GDD and late frosts

The incurrence of late frosts might cause severe damage to apple trees during the blooming season. Since our data comprise farms from different areas of Northern Italy and different altitudes, simply counting the number of days with negative temperatures in early to late spring cannot be used as reliable measure of how intensely this phenomenon can undermine yields. The main reason lies in the different timing blossoming might begin in more rigid or temperate areas, with the former being more likely to exhibit low temperatures until as late as April which, in general, delay the appearance of the first flowers. We therefore devise a synthetic indicator based on the GDDs of apple trees. Since blooming typically begins as soon as the plant has accumulated, on average, roughly 200 degree-days (WTFRC, 2014), damage from late frost can only occur at the onset of this phenological phase. Therefore, we count the days with temperatures below zero Celsius after the exact time in which the 200th degree-day was observed. The resulting measure will therefore account for spatially heterogeneous orchards, some of which may reach the target GDD much later than the others.

4 Temperature refers to the '*Temperature of air at 2m above the surface of land, sea or in-land waters. 2m temperature is calculated by interpolating between the lowest model level and the Earth's surface, taking account of the atmospheric conditions*'.

5 Total precipitation is defined as: '*Accumulated liquid and frozen water, including rain and snow, that falls to the Earth's surface. It is the sum of large-scale precipitation (that precipitation which is generated by large-scale weather patterns, such as troughs and cold fronts) and convective precipitation (generated by convection which occurs when air at lower levels in the atmosphere is warmer and less dense than the air above, so it rises). Precipitation variables do not include fog, dew or the precipitation that evaporates in the atmosphere before it lands at the surface of the Earth. This variable is accumulated from the beginning of the forecast time to the end of the forecast step. The units of precipitation are depth in meters. It is the depth the water would have if it were spread evenly over the grid box. Care should be taken when comparing model variables with observations, because observations are often local to a particular point in space and time, rather than representing averages over a model grid box and model time step*'.

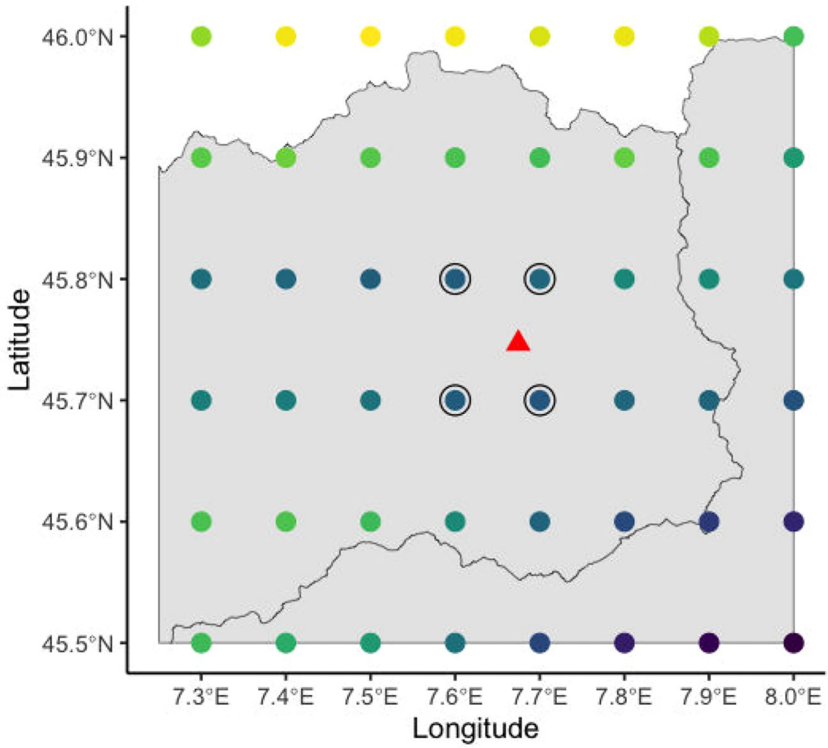


Fig. 1. Spatial matching algorithm to combine FADN and weather data.
Note: Each point corresponds to a grid vertex, while the red triangle represents the centroid of a randomly selected farm. The four circled dots indicate which meteorological observations will be used to perform the imputation.

Unlike most applied works in literature, we do not use approximate functionals to calculate GDD (Schlenker and Roberts, 2009; D'Agostino and Schlenker, 2016). Instead, we exploit the richness of our meteorological data to come up with a more precise estimate of daily growing degree-hours, which we then scale by a factor of 24 to produce GDDs. Specifically, our proposed method seeks to approximate the integral

$$\mathrm{GDD}_t = 24^{-1} \int_{h_1(t)}^{h_2(t)} dh\,[\mathcal{T}(t,h) - b] \tag{7}$$

using deterministic quadrature based on spline interpolation. Specifically, t indicates the day, $\mathcal{T}_t(h)$ is the temperature in hour h, b is a crop-specific temperature threshold (4.4°C in the case of apple trees–Rea and Eccel, 2006), $h_1(t)$ and $h_2(t)$ represent the first and the last hour for which $\mathcal{T}(t,h) > b$. Conceptually, our approach to calculating GDD is in line with the observations in Gu (2016), who discusses the potential loss of precision when using daily summaries to calculate GDDs (see, for instance, Schlenker and Roberts,

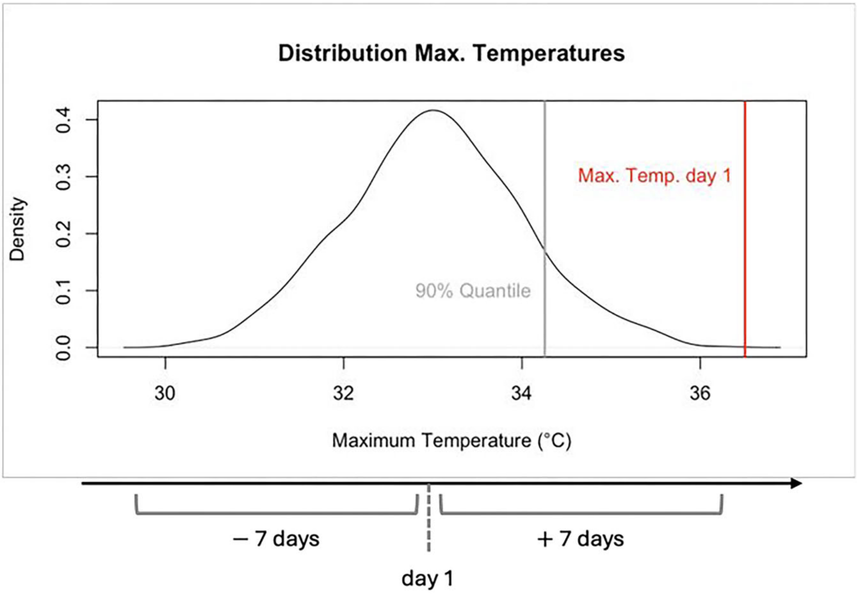


Fig. 2. Sliding window approach to calculating the CTX90pct index.

2009; D'Agostino and Schlenker, 2016), especially when more detailed data is available.

We begin cumulating GDD starting from $t = 1 =$ January 1st and proceed until $\sum_{t=1}^{T(200)} \text{GDD}_t = 200$. Once $T(200)$ is determined, we simply define a binary indicator $LF_t = \mathbb{I}\{\mathcal{T}(t) < 0\}$ for $T(200) < t <$ June 30 and calculate $LF_y = \sum_{t>T(200)}^{\text{June 30}} LF_t$ where y indicates one year between 2015 and 2020. Since the empirical distribution of LF_y is heavily right skewed with only few late frosts occurring per year, we calculate a binary variable that equals one whenever $LF_y > 0$ and zero otherwise.

3.1.2 Heat waves and precipitations

We characterize heat waves following the approach discussed in Zanotelli *et al.* (2022). Specifically, we focus on the June-August trimester and use temperature peaks to calculate the CTX90pct index proposed by Perkins and Alexander (2013). The latter suggests constructing 15-day sliding windows centred at each summer day, which provides the necessary observations to estimate the local distribution of maximum temperatures. For these empirical distributions, we calculate the 90 per cent quantiles and compare them to the temperature value registered at the midpoint of the windows themselves. A heat wave is then identified if the observed maximum temperature exceeds the 90 per cent quantile for at least three days in a row (Perkins, 2015). Figure 2 provides a simple sketch of how this system works.

We finally compute the number of heatwaves per year as simply the sum of the heatwaves detected throughout the summer season of a given year.

Precipitations can also be problematic during the spring-summer season, as prolonged rainfalls can foster pest infestations that, if not timely treated, may compromise apple yields (Zaller *et al.*, 2023). For this reason, we calculate the cumulated precipitations between April and June and include them into the estimated models using a quadratic term. The latter reflects the non-linear association between yields and rainfalls, where moderate rain is necessary to guarantee plants' sustenance, while excess precipitations can quickly become problematic.

3.2 Farm-level data

We use individual farm-level data from the Italian FADN (FADN-RICA), spanning in the period from 2015 to 2020. We selected this time frame so to ensure that all the observations fell within the same Common Agricultural Policy (CAP) framework (CAP 2014–2020). The Italian FADN collects detailed structural, economic and financial information from a sample of about 11,000 farms (across different industries) selected annually to reflect the heterogeneity of Italian agriculture in terms of production orientation, geographical distribution and farm size. We highlight that the FADN sample is not intended to represent the entire universe of farms recorded in national censuses or registers. Rather, it focuses exclusively on farms that meet a minimum economic threshold—defined as an annual economic value of at least EUR 4000—thus capturing only those holdings that are professional and market-oriented. The sub-sample of apple-producing farms for the period 2015–2020, included 678 farms in the raw dataset. We applied a series of selection criteria to isolate conventional, irrigated apple farms in Northern Italy where apple production is a core activity. These can be summarized as follows:

I. We excluded farms that allocated less than 15 per cent of their agricultural land to apple production (removing 33.36 per cent of the original sample), as we focus on farms where apple production is not a marginal activity. This left us with 452 farms.
II. We excluded farms located in Central or Southern Italy (−6 per cent of the 452), due to differing pedo-climatic conditions, resulting in 423 farms.
III. We excluded organic farms (−11 per cent of the 423). Moreover, following previous literature (De Salvo *et al.*, 2013) we also excluded those not using irrigation (−15 per cent of the remaining 377), due to differences in technology and management practices. After this step, 320 farms remained in the sample.
IV. We removed one farm reporting zero land or zero revenue, likely due to data entry errors, leaving 319 farms.
V. We excluded farms that appear only once in the panel (−5 per cent of the 319) to ensure a valid panel structure, resulting in a final panel of 303 apple-producing farms to be representative of the segment of Italian

apple farms that are economically relevant, professionally managed and actively participating in the market.

According to the Italian National Institute of Statistics (ISTAT), there are around 20,488 farms in Northern Italy with land dedicated to apple production.[6] By applying the same selection percentages observed in our analysis to this population figure—and assuming these percentages reflect the broader population—we can estimate the number of Italian apple farms meeting our selection criteria. However, it is important to note that we do not know how many of the 20,488 apple-producing farms reported by ISTAT have an economic size below the threshold criterion of €4,000 to be included in the FADN dataset. Moreover, our sample excludes farms that do not follow a panel structure—that is, those that appear only once in the dataset. Taking into account these limitations and applying the above-described selection criterion, we estimate that approximately 10,328 Italian apple farms would meet our criteria. This implies that our final analytical sample of 303 farms represents roughly 3 per cent of the relevant farm population.

Table 1 provides details on the sample farm characteristics. 79 per cent of the farms are located in the Trentino-Alto Adige region, with the remainder distributed among Emilia-Romagna, Friuli-Venezia-Giulia, Lombardia, Piemonte, Valle d'Aosta and Veneto. This distribution of farms reflects the national data for Italy, where the provinces of Bolzano (Alto Adige) and Trento (Trentino) alone account for 49 per cent of the total national production area (Ismea, 2023). The most cultivated apple variety is Golden Delicious, a PDO-protected variety, which accounts for 23 per cent of total apple production when summing across its different varieties. Consistent with this, 21 per cent of farms in our sample hold a PDO certification. The average farm size is 4.94 hectares of land. The sample is highly specialized in apple production, as the proportion of total acreage devoted to apples is 75 per cent. In addition, we estimated the average age of the orchards to be 13 years, which indicates a relatively young orchard, considering that an apple tree is considered mature around 20 years old (Bouma *et al.*, 2001).

Definitions and summary statistics for the variables used in our estimations are reported in Table 2; all the input data and the outcome variables are normalized by the amount of land devoted to apple cultivation. The two dependent variables in our model are the apple yield and the revenue per hectare from apple production. The average yield in our sample is 48 ton/ha producing a revenue of approximately 19,500 euro/ha. We have aggregated the three main fertilizers (nitrogen, phosphorus and potassium) and use the total fertilizer applications per hectare of apple (in kg) as input measure. The mean value of this variable in our sample is 304 kg/ha with a high heterogeneity

6 Author's elaboration on ISTAT data (retrieved on October 28, 2025). The most recent year available for this dataset is 2016. Source: The regions included in the analysis are Trentino-Alto Adige/Südtirol, Piemonte, Emilia-Romagna, Veneto, Lombardia, Friuli-Venezia Giulia and Valle d'Aosta/Vallée d'Aoste.

Table 1. Farm characteristics in our sample.

Geographical Location-Region (% of farms in our sample)	
Trentino Alto Adige/Südtirol	79%
Piemonte	10%
Valle D'Aosta/Vallée d'Aoste	4%
Lombardia	1%
Emilia Romagna	2%
Veneto	1%
Friuli Venezia Giulia	2%
Variety of Apple Crop (% of farms in our sample)	
Fuji	4%
Golden Delicious	23%
Mondial gala	1%
Pink Lady	5%
Red Chief	4%
Renetta	3%
Royal Gala	4%
Other/Not specified	56%
Geographical indication (% of farms in our sample)	
PDO Certification	21%
PGI Certification	2%
No Certification	77%
Orchard Age	
Mean (SD)	13.15 (4.56)
Min–Max	3.06–36.5
Land cultivated (hectares)	
Mean (SD)	4.94 (3.86)
Min–Max	0.2–31.92
Share of farmland allocated to apple production	
Mean (SD)	0.75 (0.27)
Min–Max	0.15–1

across farms. The high heterogeneity is explained by the fact that the fertilizer requirements of apples are much higher in the first year of planting than in later years. While fertilizers and labour are expressed in physical units (kg and hours respectively), pesticides are expressed in monetary terms and the average value in the sample is 1,247 euro/ha.

4. Results

Table 3 reports the estimation results for the yield and revenue per hectare models. Columns 1, 2 and 3 show the results for the mean, variance and semi-variance of yield and Columns 4, 5 and 6 show the corresponding results for revenue per hectare. Since we used a quadratic production function

Table 2. Conventional inputs and weather variables—descriptive statistics.

Variable [a]	Definition (unit of measurement)	Mean	SD	Min	Max
	Output				
Revenue per hectare [b]	Revenue per hectare (€/ha)	19,562.20	11,224.17	137.86	70,595.30
Yield	Yield (Ton/ha)	48.13	20.35	0.422	116.42
	Agricultural input				
Expenditure for pesticides [b]	Expenditure for pesticides (€/ha)	1246.98	687.036	11.589	8800
Quantity of fertilizers	Sum of nitrogen, phosphorus and potassium (Kg/ha)	303.59	331.30	0	5803.76
Labor (hours/year) per hectare [c]	Total sum of hours contributed by both employees (including machine and man hours) and family labour (including machine and man hours (hours/ha)	817.95	362.48	128.33	3243.25
	Weather variables				
Late Frost 200GDD	Binary variable which takes on the value of 1 if there are days with temperatures at or below 0 degrees C° following the accumulation of 200 GDD.	0.35		0	1
Heat waves	Number of heat waves per year.	12.22	3.16	5.50	26.27
April–June rainfall	Total precipitation accumulation during the period spanning from April 1st to June 30th (mm)	396.60	98.12	108.65	706.28
Number of farms	303				
Number of observations	1383				

[a] Data not standardized.
[b] Monetary variables were adjusted for inflation utilizing Eurostat agricultural output and input price indices.
[c] Due to the lack of crop-specific labour data in the FADN dataset, the variable labour (hours) per hectare was calculated taking into account all the hectares of the farm, not only those with apple trees. Conversely, all other variables are crop-specific and have been calculated dividing by the number of apple hectares.

Table 3. Estimation results of the yield and revenue per hectare models.

	Yield			*Revenue per hectare*		
	Expected value	Other moments estimated coefficients		Expected value	Other moments estimated coefficients	
	[1] Elasticity at the mean	[2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	[5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.162***	−0.022	−0.063**	0.128***	−0.034	−0.044**
	(0.031)	(0.019)	(0.027)	(0.041)	(0.021)	(0.020)
Fertilizers	0.047**	0.015	0.015	0.007	0.029	0.037
	(0.015)	(0.016)	(0.022)	(0.022)	(0.021)	(0.027)
Labour	0.492***	0.051	0.091	0.392***	0.023	0.048
	(0.062)	(0.047)	(0.102)	(0.082)	(0.023)	(0.034)
Weather variables—Estimated Coefficients						
Late Frost 200GDD	−0.087*	0.109**	0.241***	0.187***	0.001	0.021
	(0.052)	(0.043)	(0.081)	(0.063)	(0.047)	(0.05)
Heat waves	0.028	0.012	0.001	−0.005	−0.110***	−0.080***
	(0.039)	(0.028)	(0.051)	(0.035)	(0.024)	(0.029)
Precipitation April-June	0.028	0.002	0.009	−0.168***	−0.107***	−0.048*
	(0.036)	(0.021)	(0.039)	(0.037)	(0.023)	(0.028)
Precipitation April–June squared	−0.006	0.010	0.014	0.054***	0.010	0.01
	(0.015)	(0.014)	(0.023)	(0.019)	(0.015)	(0.015)
Individual fixed effects	Yes	–	–	Yes	–	–
Time fixed effects	Yes	–	–	Yes	–	–
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1.383	1.383	664	1.383	1.383	703
F Statistics	11.416***	1.814*	2.141**	6.360***	8.678***	3,475
	(df = 13; 1,062)	(df = 7; 1,375)	(df = 7; 655)	(df = 13; 1,062)	(df = 7; 1,375)	(df = 7, 695)

All Models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

(which includes inputs in original units, squared units and interaction terms) we report elasticities rather than estimated coefficients for the expected yield and expected revenue equations (Columns 1 and 4). The original estimated coefficients are reported in Table B1 in Appendix B. In addition, we check for robustness of the main model with a battery of models (see Tables B2–B12 in Appendix B), in which we vary the inclusion of the weather variables and of the fixed effects (time fixed effects, individual fixed effects, agrarian-region fixed effects[7]).

4.1 Results on the relationship between pesticide expenditure and crop output

In this section, we examine the association between pesticide expenditure and the two outcome variables employed in our models: yield and revenue per hectare.

Focusing first on expected yield value (Column 1, Table 3), we find that the yield elasticity with respect to pesticide expenditure is positive and statistically significant, indicating that a 10 per cent increase in pesticide expenditure is associated with an average 1.6 per cent increase in crop yield. This positive association is consistent with previous literature (Babcock *et al.*, 1992; Zaller *et al.*, 2023). Instead, when considering the second moment of the distribution—the variance (Column 2)—we find that pesticide expenditure is not statistically significantly associated with the variance of apple yield. However, a focus on variance would not give us a realistic picture of the decision-making process of risk-averse farmers (Di Falco and Chavas, 2006), as variance alone does not allow us to distinguish between upside and downside risk. To this end, we examined the coefficients of the negative semi-variance of yield (Column 3). Our results indicate lower values of yield semi-variance when comparing two observations that differ by one unit of pesticide expenditure, which would imply a reduction in the variation below the mean. Thus, a higher level of pesticide expenditure in apple production is associated with a lower level of downside risk. This result is consistent with previous studies that have used expenditure as a proxy for pesticide use and found the same direction of correlation (Koundouri *et al.*, 2009; Skevas *et al.*, 2014; Gong *et al.*, 2016; Praneetvatakul *et al.*, 2016).

Turning to revenue per hectare, our results show that the elasticity of the expected value of revenue per hectare with respect to pesticide expenditure is positive and statistically significant (Column 4, Table 3): a 10 per cent increase in pesticide expenditure is associated with an average 1.3 per cent increase in revenue per hectare. However, as observed for yield, there is no significant correlation between pesticide expenditure and revenue-per-hectare variance (Column 5). Again, to gain real insight into the welfare of a risk-averse farmer,

7 The agricultural region is a territorial subdivision used in the Italian FADN, defined as a homogenous area composed of neighbouring municipalities within the same province whose lands share similar natural (i.e. climate, geology, topography) and agricultural (i.e. cropping systems) characteristics

we considered, also in this case, the negative semi-variance. Our results, here, are consistent with yield, with pesticides being negatively associated with the downside risk of revenue. One possible explanation for this is that plant protection measures affect not only yield but also quality (Babcock *et al.*, 1992; Zachmann *et al.*, 2024a), and since lower quality often leads to lower prices (Frisvold, 2019), the use of pesticides can be used not only as a strategy to ensure a good yield but also to obtain better looking apples (Zachmann *et al.*, 2024a).

4.2 Results on the relationship between weather variables and crop output

Not being input to the production function and therefore exogenous to farmer's behaviour, one can reasonably assume that weather variables could be either partially or fully exogenous in in our econometric specification. For this reason, this section reports and discussed the estimated associations between the outcome and weather variables, even though a transparent identification strategy is missing.

Examining the results for weather variables and the expected yield (Column 1), we find that our results are consistent with those of previous studies (Singh *et al.*, 2016; Unterberger *et al.*, 2018; Pfleiderer *et al.*, 2019). Specifically, we observe a lower expected yield when comparing observations that differ by one unit in late frosts (Late Frost 200 GDD, i.e. farms that experienced late frosts versus those that did not). No significant association was found for the remaining weather measures. Considering variance (Column 2) and in line with previous literature (Di Falco *et al.*, 2014), our data show greater yield variance among farms that experienced late frosts. Finally, we observe a positive correlation between late frosts and negative semi-variance, indicating greater downside risk. This empirical evidence also aligns with existing literature on climate shocks and crop yields. In particular, Vitasse *et al.* (2018) and Wolfe *et al.* (2018) emphasize the significant threat that spring frosts related to climate change pose to agricultural production.

When considering revenue per hectare, our results indicate that late frosts are positively and significantly associated with expected revenue per hectare (0.187), in contrast to their negative association with yield (–0.087). Although counterintuitive at first, this result can be explained by the fact that revenue is derived from the quantity produced and the price received by the farmer, and weather variables are likely to affect both these components through yield and quality. Indeed, as economic theory would suggest, under the reasonable assumption of an inelastic demand for apples, we expect that a decrease in quantity (i.e. a reduction in yield due to late frost) would be smaller than the increase in price, resulting in an increase in average revenue. This result of course depends on the market structure which, as discussed in Section 3.2, is geographically concentrated, with Trentino accounting for roughly 64 per cent of total Italian apple production (Trentino alone also represents more than 79 per cent of our sample). Therefore, a negative weather event affecting production at a regional or sub-regional level is likely to affect the market equilibrium, as prices for specific apple varieties are set at the regional level. In principle, we would expect the same pattern of late frosts for rainfall, as prolonged rainfall (i.e. the quadratic term in the equation) could negatively correlate with apple yields, thus potentially increasing revenue. However, although the pattern of signs is consistent with our hypothesis, the coefficients on the expected value of rainfall on yield are not significant and so we cannot draw any definitive conclusion. The results for the revenue per-hectare variance (Column 5) show that heat waves and the linear precipitation term are negatively and significantly associated with the variance of revenue per hectare. Finally, we find that heat waves and the linear precipitation term are negatively correlated with the revenue negative semi-variance.

4.3 Robustness checks

Appendix B (Tables B2–B12), reports the results of a comprehensive set of robustness checks to test alternative specifications of the main model, which are summarized in Table 4 for the yield and in Table 5 for the revenue per hectare. For the association between pesticide expenditure and expected yield/revenue per hectare, the coefficient is consistently positive, stable in magnitude and statistically significant across all specifications. By contrast, the results for the negative semi-variance model—both for yield and for revenue per hectare—are less stable: the coefficient is not statistically significant in several specifications. Specifically, for the negative semi-variance of both yield and revenue per hectare, the coefficient cannot be distinguished from zero when individual fixed effects are removed. Moreover, in the revenue per hectare equation, we also fail to reject the null hypothesis when controls and time fixed effects are simultaneously removed. This suggests that there might be time-invariant variables that are simultaneously correlated with pesticide expenditure and the outcome variables. If these are not accounted for by fixed effects, they will undermine our conclusions. However, if we include a fixed effect for the agrarian region rather than for the farm, the coefficient remains statistically significant and its magnitude is very close to that of the main model. This suggests that the unobserved, time-invariant factors undermining our results are regional rather than individual factors, i.e. they relate to differences in pedological soil and conditions across different areas.

4.4 Sensitivity analysis and placebo tests

Table 6 shows the results of the sensitivity analysis proposed by Cinelli and Hazlett (2020), targeting the pesticide expenditure coefficients, across both outcome variables—yield and per hectare revenue—and for both model specifications: the mean and negative semi-variance equations.

The core idea of Cinelli and Hazlett (2020) builds upon the early work of Imbens (2003), as both parameterize the strength of potential unobserved confounders in terms of partial R^2 values and use the corresponding contour plots to benchmark against observed covariates. However, Cinelli and Hazlett

Table 4. Summary of robustness checks for the yield model.

Yield model					
Weather variables [a]	Individual FE [b]	Time FE	Pesticide expenditure (expected value)	Pesticide expenditure (variance)	Pesticide expenditure (negative semi-variance)
		Main model			
Y	Farm level	Y	0.162***	−0.022	−0.063**
		Robustness checks			
Only late frost excluded	Farm level	Y	0.161***	−0.019	−0.053*
Only heatwaves excluded	Farm level	Y	0.162***	−0.022	−0.063**
Only rainfall exluded	Farm level	Y	0.162***	−0.022	−0.046**
N	Farm level	Y	0.162***	−0.019	−0.047*
Y	N	N	0.276***	0.046	−0.026
N	N	N	0.287***	0.083	−0.0003
Y	Farm level	N	0.167***	−0.024	−0.077***
Y	N	Y	0.247***	0.045	−0.015
N	N	Y	0.268***	0.06	0.009
N	Farm level	N	0.181***	−0.016	−0.067**
Y	Agrarian region level	Y	0.242***	−0.02	−0.064***

FE = Fixed effects.
[a] = weather variables are late frosts, heatwaves and rainfall.
[b] = individual fixed effects are at farm level or at agrarian region level.
Y = Yes, if the weather variables/fixed effects were included in the model.
N = No, if the weather variables/fixed effect were not included.

(2020) extend Imbens's (2003) framework in two ways. First, they relax the assumption on the functional form of the treatment assignment: while Imbens's setup is restricted to a binary treatment, Cinelli and Hazlett's approach is more general and can also be applied to continuous treatments, such as pesticide expenditure in our setting. Second, Imbens's method explicitly requires assumptions about the distribution of unobservables to perform sensitivity analysis, whereas Cinelli and Hazlett's approach avoids this requirement, making the analysis simpler and more broadly applicable. Finally, the authors propose a new solution to the previously used informal bounding procedures for benchmarking unobserved confounders, which solely relied on the statistics of observed covariates. They instead formally bound the maximum strength of an unobserved confounder relative to one or more observed covariates using partial R^2, thereby allowing a formal comparison of the strength of associations.

In what follows, we adopt the notation of Cinelli and Hazlett (2020) and indicate with D the 'treatment' variable of interest (pesticide expenditure), Y in-

Table 5. Summary of robustness checks for the revenue per hectare model.

Revenue per hectare model					
Weather variables [a]	Individual FE [b]	Time FE	Pesticide expenditure (expected value)	Pesticide expenditure (variance)	Pesticide expenditure (negative semi-variance)
		Main model			
Y	Farm level	Y	0.128***	−0.034	−0.044**
		Robustness checks			
Only late frost excluded	Farm level	Y	0.129***	−0.036*	−0.044**
Only heatwaves excluded	Farm level	Y	0.127***	−0.036*	−0.043**
Only rainfall exluded	Farm level	Y	0.120***	−0.036*	−0.038*
N	Farm level	Y	0.121***	−0.043**	−0.045**
Y	N	N	0.299***	0.013	0.006
N	N	N	0.282***	−0.017	−0.0003
Y	Farm level	N	0.098**	−0.039*	−0.047***
Y	N	Y	0.274***	0.018	0.01
N	N	Y	0.254***	−0.006	0.002
N	Farm level	N	0.045**	−0.037	−0.017
Y	Agrarian region level	Y	0.258***	−0.047	−0.045**

FE = Fixed effects.
[a] = weather variables are late frosts, heatwaves and rainfall.
[b] = individual fixed effects are at farm level or at agrarian region level.
Y = Yes, if the weather variables/fixed effect was included in the model.
N = No, if the weather variables/fixed effect was not included.

dicates the outcome (i.e. either yield or revenues per hectare), Z represents an omitted confounder, while X identifies other control variables. Starting from the results for the yield outcome under Equation (5), the RV shows that, had an unobservable confounder explained less than 14.4 per cent of the residual variance in both pesticide expenditure and yield per hectare, this would not be sufficiently strong to overturn the estimated correlation. In other words, a confounder weaker than the above threshold would be insufficient to completely nullify the relationship between pesticide expenditure and yield. From an inferential perspective, at the 5 per cent significance level, the RV drops to 9.1 per cent, meaning that a confounder only one-third as strong as the observed relationship could make the correlation no longer statistically significant. To assess whether these figures are substantial, we bounded the strength of potential confounders using labour as a benchmark covariate in the model. This is because our results show that labour has the highest input elasticity for both the yield and the revenue per hectare expected value model. The correspond-

Table 6. Sensitivity analysis for the yield and per hectare revenue expected value and negative semi-variance model (Cinelli and Hazlett, 2020).

	$R^2_{Y\sim D\|X}$ (%) [a]	RV (%)	$\mathrm{RV}_{(q=1,\ \alpha=0.05)}$ (%)	$R^2_{D\sim Z\|X}$ (%) [b]	$R^2_{Y\sim Z\|X,\ D}$ (%) [b]
Yield [expected value]	2.4%	14.4%	9.1%	2.6%	6.3%
Yield [negative semi-variance]	0.8%	8.7%	1.4%	/	/
Revenue per hectare [expected value]	0.9%	8.9%	3.2%	2.6%	2.3%
Revenue per hectare [negative semi-variance]	0.7%	8.0%	0.9%	/	/

[a] The partial R^2 of the treatment with respect to the outcome, $R^2_{Y|D,X}$ (partial R^2 of the treatment with the outcome) indicates the proportion of outcome variance uniquely explained by the treatment. In a worst-case sensitivity analysis, unobserved confounders would need to explain at least this proportion of the residual variance in the treatment to fully nullify the effect. In the yield model, $R^2_{Y\sim D|X}$ =2.4 per cent which is below the bound $R^2_{D\sim Z|X}$(per cent) = 2.6 per cent. Similarly, for revenue, $R^2_{Y\sim D|X}$ = 0.9 is below $R^2_{D\sim Z|X}$(per cent) = 2.6 per cent. Thus, in either case, we cannot rule out the existence of a 'worst-case confounder' explaining all the left out-variance of yield (revenue) and as strongly associated with the pesticide expenditure as labour per hectare. However, we reasonably assume that the existence of such strong confounders is unlikely in a framework like ours, where we already control for potential unobserved heterogeneity through the inclusion of both individual and time fixed effects.

[b] Selected bound: Labour per hectare.

ing partial R^2 after controlling for X, D and X, which indicate the strength of a confounding factor as strong as labour per hectare, are $R^2_{Y\sim Z|X,D} = 6.3$ per cent and $R^2_{D\sim Z|X}= 2.6$ per cent, respectively. Since the RV is greater than both of these values, we can conclude that a confounder as strong as labour per hectare would not be sufficient to explain away the observed correlation of pesticide expenditure with crop yield.

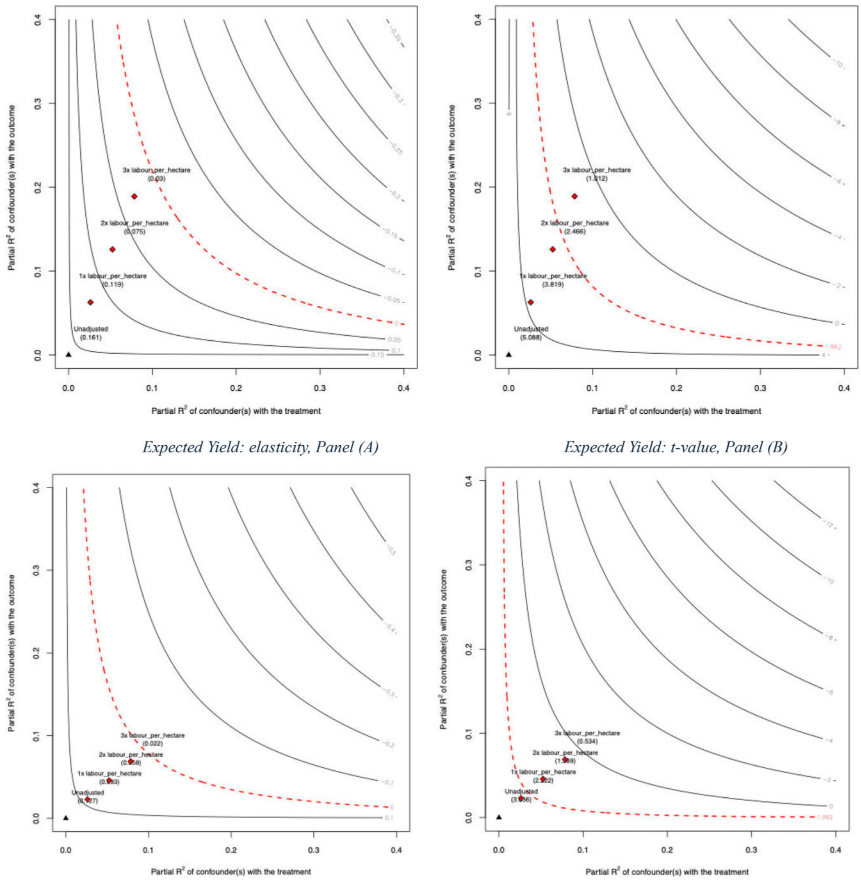
We obtain comparable results when switching to the per-hectare revenue expected value model, where the RV is 8.9 per cent. The RV drops to 3.2 per cent when accounting for statistical significance at the 95 per cent confidence level. This suggest that the direction of the estimated correlation appears reasonably robust, although the estimated coefficient would decrease to the point that the corresponding t-statistics fail to reject the null hypothesis of no correlation.

Turning to the analysis of the negative semi-variance, the RV of the pesticide expenditure coefficients in the per-hectare revenue model is consistent with the RV obtained for the mean equation. On the other hand, the RV for the yield outcome is considerably lower than the one obtained for the expected value model. However, these values are very similar for both outcomes, with RVs of 8.7 per cent and 8.9 per cent, respectively. We note, however, that the RVs decrease substantially when considering statistical significance at the 95 per cent confidence level—suggesting that potential unobserved confounding is likely to quickly deflate *t*-values and make rejecting the null hypothesis of zero correlation less likely [8].

The bounding exercise we conducted for the expected value equations enabled us to construct the sensitivity contour plots shown in Fig. 3. The points on the plot indicate the bounds on the partial R^2 of a hypothetical unobserved confounder if it were k times stronger than the observed covariate labour per hectare. The first point shows the bounds for a confounder as strong as labour per hectare. A second reference point shows the bounds for confounders twice as strong as labour per hectare, and finally the last point bounds the strength of confounders three times as strong as labour per hectare. Panel (A) shows that the sign of the point estimate is robust to confounding up to three times the strength of labour per hectare in the expected yield equation. However, it is important to note that the magnitude of the coefficient shrinks as the bound increases, indicating that the stronger the hypothetical unobserved confounder, the smaller the magnitude of the estimated association, which nevertheless remains positive.

Turning to inference, Panel (B) illustrates the sensitivity of the *t*-value of the pesticide coefficient in the expected yield equation. Using the benchmark of labour per hectare, the estimate of pesticide expenditure would remain sta-

8 For the semi-variance models, we chose not to use a benchmark confounder. This decision is based on the observation that if the chosen benchmark is not a strong predictor of either outcome or treatment, the bounding exercise becomes uninformative. While it is possible to apply domain knowledge to the mean function, we argue that doing so is much more difficult in the context of modelling risk, and thus we preferred to report only the RVs (Cinelli and Hazlett, 2020; Kugler, 2022).



Expected Yield: elasticity, Panel (A)

Expected Yield: t-value, Panel (B)

Expected Revenue per hectare: elasticity, Panel (C)

Expected Revenue per hectare: t-value, Panel (D)

Fig. 3. Sensitivity contour plots in the partial R^2 scale with benchmark bounds.
Note: Panel A, C report the sensitivity contour plots of the point estimate, respectively for the expected yield and expected revenue per hectare. Panel B, D report sensitivity contour plot of the *t*-value respectively for the expected yield and expected revenue per hectare.

tistically significant under unobserved confounders up to twice as strong. Instead, under confounders three times stronger than the benchmark covariate, the coefficient would no longer be statistically significant. Panel (C) shows that the sign of the pesticide expenditure point estimate is robust to confounding up to three times the strength of labour per hectare in the expected revenue equation. As in the case of yield per hectare, the magnitude of the coefficient decreases as the bound increases, that is, in the presence of an unobserved confounder stronger than labour per hectare. However, when considering inference (Panel D), the estimated coefficient in the revenue equation remains statistically significant only when accounting for a confounding factor equiva-

Table 7. Oster test results.

	Yield		*Revenue per hectare*	
	Expected value	Negative semi-variance	Expected value	Negative semi-variance
β	0	0	0	0
$\lvert\delta\rvert$	2.02	5.18	2.12	28.2
$R^2_{\max}$	0.69	0.03	0.72	0.04

lent in strength to labour per hectare. When confounders twice or three times as strong are considered, the estimated association between pesticide expenditure and revenue is no longer statistically significant. By contrast, the results for yield suggest that the estimates would remain significant in the presence of confounders up to twice as strong as labour per hectare.

Finally, the RV of the *t*-values for the two negative semi-variance equations indicates that their sensitiveness to potential omitted confounders is much stronger than for the corresponding expected value models.

As a second test to probe the sensitivity of pesticide expenditure to OVB, we applied the approach proposed by Oster (2019) to both mean and negative semi-variance equations for the yield and per-hectare revenue outcome variables. To make statements on the robustness of the coefficients we report the indicator $|\delta|$, which indicates the relative importance of selection on unobservables versus observables, that is the value that would be required to shrink the estimated coefficient to zero (i.e. to 'explain away' the result). According to Oster (2019, if the $|\delta| > 1$, then the influence of unobservables on the results is limited. To determine $|\delta|$ we must set a value for $R^2_{\max}$ which is the R^2 obtained from a hypothetical regression of the outcome variable on all potential unobservables and observables covariates. To do so, we followed Oster rule of thumb of $R^2_{\max} = 1.3\tilde{R}$, where $\tilde{R}$ is the R^2 obtained from the regression with the observed controls. The results in Table 7 indicate that in the yield model, selection on unobservables would need to be at least 2.02 and 5.18 times stronger than selection on observables in order to fully eliminate the estimated correlation of pesticide expenditure with the expected value and the negative semi-variance of yield and revenue, respectively. For the revenue per hectare model, the Oster test results suggest that selection on unobservables would need to be 2.12 and 28.2 times stronger than selection on observables in the expected value and negative semi-variance equations, respectively, to control the significant relationship away. The very high values for the negative semi-variance equation are most likely the result of the very low R-squared, which suggests caution when interpreting the results of this testing procedure for these models.

The last sensitivity analysis builds upon the procedure discussed in Stetter *et al.* (2022) and Coderoni *et al.* (2024) (SC22-24 for brevity). This consists in generating an unobserved confounder $Z \sim N(0, 1)$ such that the partial correlations between the latter and both outcomes (i.e. per-hectare expenditure or yield) and the treatment variable (i.e. pesticide expenditure) are set to pre-determined values $\rho_{Y\sim Z|X,D} \in (-1, 1)$ and $\rho_{D\sim Z|X} \in (-1, 1)$, respectively. The resulting synthetic variable is then incorporated into the set of control variables for both the expected value and negative semi-variance models, from which we obtain new estimates of the relevant elasticities. For space reasons we only report the details and full results of this methods in Appendix C (Fig. C1 and C2). Results are in line with those obtained via the Cinelli and Hazlett (2020) procedure, in that the revenue expected value equation seems more sensitive to unobserved confounder than the expected value equation for the yield outcome. However, we find that the negative-semi-variance models tend to be approximately as robust to omitted variables, which appears more in line with the results obtained with the Cinelli and Hazlett (2020) test for the yield equation.

We finally conduct two simple placebo tests to probe the resilience of our estimates to potentially unobserved confounder(s). Using the terminology discussed in Eggers *et al.* (2024), the latter can be assessed through placebo outcome and placebo treatment tests, each designed to falsify the unconfoundedness assumption by tackling different components of the underlying causal diagram. Specifically, an outcome placebo test aims at finding an alternative outcome variable, $\tilde{Y}$, that is caused by Z but on which the treatment has no impact. Therefore, finding an association between $\tilde{Y}$ and D would call identification into question. In this work, we choose the yield and the revenue of other non-apple crops as placebo outcomes. The reason is straightforward: we assume that the unobserved factors that potentially confound the pesticide-yield (pesticide-revenue) relationship for apples, also influence the distribution of the yield (revenue) variable for other crops. Next, a treatment placebo test requires an alternative treatment variable, $\tilde{D}$, whose adoption critically depends on Z, but does not affect the distribution of Y. Coherently with the choice of placebo outcome, a natural choice of placebo treatment is the application of pesticides to other crops on the farm that are not apples. Therefore, any non-zero effect of the placebo treatment on apple yields or revenues would challenge the identification strategy. Results for the two placebo tests are reported in Table D1 and D2 in Appendix D. On the one hand, the outcome placebo test (Table D1) indicates that pesticide expenditure is uncorrelated with the mean revenue of non-apple crops and also shows no association with the negative semi-variance of yield and revenue. However, we find a statistically significant association between $\tilde{Y}$ and D in the expected yield equation, indicating potential identification issues when it comes to the effect of pesticide expenditure on this outcome variable. On the other hand, the placebo treatment test indicates no association between $\tilde{D}$ and the expected value of Y for both outcomes of interest. Conversely, we find potential correlation between the placebo treatment and the negative semi-variance of both yield and per-hectare revenues, indicating that OVB could potentially be problematic when characterizing risk behaviour.

Table 8. Summary of sensitivity test results.

		Yield		*Revenue per hectare*	
Test	Object	*Expected value*	*Negative S.V.*	*Expected value*	*Negative S.V.*
Cinelli and Hazlett (2020)	Point estimate	Good	Fair	Fair	Fair
Cinelli & Hazlett (2020)	*t*-value	Good	Bad	Fair	Bad
Oster (2019)	Point estimate	Good	Good[a]	Good	Good[a]
SC22-24	Point estimate	Good	Good	Fair	Good
Placebo treatment	Point estimate	Good	Bad	Good	Bad
Placebo outcome	Point estimate	Bad	Good	Good	Good

[a]This result must be used with caution.

We qualitatively summarize all the results from the sensitivity and placebo tests in Table 8, where each outcome is ranked based on the degree to which it challenges (i.e. a Bad result) identification. Even though, a Bad-Fair-Good scale is arbitrary and does not fully capture the nuance of the tests, it does however provide a more concise picture of main results to guide the discussion in the following Section.

5. Discussion and conclusions

In this study, we assessed the correlation between pesticide expenditure and expected yield and revenue, as well as the potential association between pesticide expenditure and the negative semi-variance of yield and revenue, in apple production in Northern Italy. The negative semi-variance is an important variable in the agricultural economics domain as it approximates the downside risk experienced by the farmer.

Our results show that the expected values of yield and revenue per hectare are positively associated with pesticide expenditure, indicating that higher pesticide use is linked to higher yield and revenue (Babcock *et al.*, 1992; Zaller *et al.*, 2023). In contrast, when considering downside risk, we find a negative association between pesticide expenditure and the semi-variance of yield and revenue per hectare. Thus, according to our findings—and consistent with a stream of literature using expenditure as a proxy for pesticide use (Koundouri *et al.*, 2009; Skevas *et al.*, 2014; Gong *et al.*, 2016; Praneetvatakul *et al.*, 2016)—pesticides can be classified as a downside risk–reducing input in apple production in the Northern Italian context. However, this classification should be interpreted with caution in light of the results of several sensitivity analyses.

In fact, while the sensitivity analyses reveal that the expected value models are moderately robust to hypothetical unobservables—with the yield model being less sensitive than the revenue model—the results show that the results from the semi-variance equations are more sensitive to unobserved confounders, particularly with regard to inference (see Table 8). In practice, our tests suggest that potential unobserved confounders could easily reduce the *t*-values, resulting in failing to reject the corresponding null hypotheses that the pesticide expenditure correlates with the negative semi-variance equations, particularly in the revenue per hectare model. The placebo treatment tests, too, point in this direction, suggesting potential identification issues when it comes to the exogeneity of the treatment assignment mechanisms. Overall, these figures imply that relying on individual and time fixed effects, with weather variables proxying for unobservable factors such as pest pressure and the stochasticity of crop growth, could be sufficient for reliably estimating a causal effect of pesticide expenditure on expected values of yield and per-hectare revenue (even though the yield equation fails to satisfy the corresponding placebo outcome test). In the case of the semi-variance model, we cannot claim any causal effect with a high degree of confidence. Instead, we should talk simply about a correlation between pesticide expenditure and the semi-variance of apple production. These are all important consideration when interpreting our findings, as they highlight the complexity of identifying the relationship between pesticide expenditure and farmers' exposure to downside risk even after applying well-established econometric estimation techniques.

That said, while our results are specific to the geographical context of the study and warrant caution in light of the numerous sensitivity checks, they suggest that pesticides are associated with a lower level of downside risk in apple production. Although heavily reliant on stringent identifying assumptions and representing, for the most, simple (although carefully addressed) correlation patterns, these finding can still provide useful information for the design of pesticide regulations targeting apple cultivation, or at least indicating a clear direction for further research. Indeed, finding effective solutions to make apple growing more sustainable is particularly challenging. Since apples are a perennial crop, adopting practices such as introducing resistant varieties or changing the cultivar mixture would mean that growers will only see tangible results in the medium or long run. Furthermore, apple growers often engage in preventive pesticide application, which implies that farmers must make decisions under uncertainty, without knowing the timing or intensity of potential infestations (Finger *et al.*, 2024). This, compounded by the likely association between a higher level of pesticide application and a lower level of downside risk, creates a complex environment that challenges farmers' ability to make fully rational decisions.

Our results provide empirical evidence consistent with expectations about farmers' behaviour and decision-making under uncertainty formulated in theoretical models (Hardaker *et al.*, 2004). More specifically, conditional on the sensitivity-analysis results, the finding that pesticide use reduces downside risk suggests that risk-averse farmers may consider pesticides as risk management tool and therefore apply them preventively within an uncertain decision-making environment (Hardaker *et al.*, 2004). This interpretation is consistent with the idea that input-use decisions are shaped not only by agronomic conditions, but also by farmers' risk attitudes, accumulated experience in dealing with adverse events, and their subjective beliefs about the likelihood and severity of such events (Flaten *et al.*, 2005; Lien *et al.*, 2022). In line with this view, Lien *et al.* (2022) stress that heterogeneity in risk preferences and risk perceptions helps explain systematic differences in crop-protection strategies across farming systems. Seen through this lens, the consequences of adverse events depend not only on the events themselves, but also on how farmers anticipate, prepare for, and manage risk. In uncertain decision-making contexts, farmers' risk preferences can become even more salient than deliberative, '*rational*' decision processes. This can keep growers anchored to the status quo—default risk-management strategies and familiar practices—rather than experimenting with newer, potentially more sustainable alternatives (Finger *et al.*, 2024; Dalhaus *et al.*, 2024). Therefore, in order to avoid over-application of chemicals, the primary policy objective at the farm level should be to support farmers in reducing the uncertainty and risk of farming. This can be achieved by promoting the adoption and effective use of decision-support systems (DSS), expanding knowledge and training on alternative risk-mitigation practices (e.g. integrated pest management), and improving access to tools and technologies that increase the reliability of non-chemical strategies (Lien *et al.*, 2022).

DSS should reduce uncertainty regarding risk and time, helping farmers to anticipate plausible short- and long-term scenarios (Finger *et al.*, 2024, Finger et al., 2023). This is an even more pressing need given our additional results discussed on extreme weather events. In particular, late frosts, which found positively correlated with downside risk in the yield equation, may become more frequent in the future (Lamichhane, 2021), and extreme weather events can hinder efforts to reduce pesticide use (Zaller *et al.*, 2023). Although DSS have been shown to be effective in helping apple growers to determine the appropriate timing and quantity of pesticide application, thus implementing sustainable crop protection without compromising yield (e.g. Jones *et al.*, 2010; Mondino and González-Andújar, 2019; Padma *et al.*, 2017), uptake remains low (Lefebvre *et al.*, 2024; Marinko *et al.*, 2025) mostly due to factors related to growers risk aversion and lack of proper information (Gent *et al.*, 2011; Lázaro *et al.*, 2021; Lefebvre *et al.*, 2024). Furthermore, even when DSS are adopted, they are not guaranteed to be effective, as farmers often deviate from the recommended choices when making decisions in practice (Möhring *et al.*, 2020a). Agricultural policies can thus support the adoption and proper use of DSS by: (i) offering education and training through agricultural schools (Marinko *et al.*, 2025); (ii) strengthening system credibility by expanding access to timely, spatially explicit data on weather conditions and disease outbreaks (Lázaro *et al.*, 2021; Möhring *et al.*, 2020a); (iii) involving growers in DSS design and testing through participatory approaches (Lázaro *et al.*, 2021) and (iv) introduce a green insurance scheme that compensates farmers for yield losses when, despite implementing best risk management practices (i.e.

following DSS recommendations), pest or disease outbreaks are not successfully contained (Lefebvre *et al.*, 2024).

However, we stress that increasing and improving the use of DSS alone is unlikely to be sufficient; such tools should not be viewed in isolation but as part of a broader transition towards an effective sustainable crop protection strategy (Finger *et al.*, 2024).

To this end, we argue that the transition towards reduced pesticides should adopt a holistic approach—engaging all relevant actors along the supply chain—rather than focusing solely on enforcing individual policy goals (Möhring *et al.*, 2020a). Given that a large share of pesticides used in apple production serves a cosmetic purpose (Zachmann *et al.*, 2024a), a supply-chain approach could include working to modify the marketing standards for apples. These standards define the quality grading of fruit and vegetables, including apples, and rely heavily on cosmetic specifications to assign the highest quality grade, and thus the highest market premium price. For example, the Commission Delegated Regulation 2021/1890 states apples '*[...]must be free from defects with the exception of very slight superficial defects provided these do not affect the general appearance of the produce, the quality, the keeping quality and presentation in the package[...]*', in order to obtain Extra-A grading. Revising these standards so that quality is not primarily determined by cosmetic appearance would be an important step towards reducing the use of pesticides for aesthetic purposes. Such a reform should be accompanied by clear communication with consumers, for example by providing point-of-sale information explaining why produce may appear imperfect, and promoting its nutritional value rather than its appearance (Zachmann *et al.*, 2024a).

In conclusion, we agree with Möhring *et al.* (2020b) that the key priority for the EU is not only to develop more effective pesticide reduction policies, but also to revise its pesticide regulatory framework. A shift from a hazard-based approach to a risk-based assessment is urgently needed, as current policy objectives based on quantitative indicators of pesticide use risk are likely to lead to unintended consequences. Such indicators often underestimate the true risks associated with pesticide use and, in some cases, may encourage the use of low-dose pesticides that are highly effective against target pests but have greater ecotoxicological effects on non-target organisms (Möhring *et al.*, 2020b).

Finally, we offer a consideration regarding our empirical approach and highlight the study's limitations. In line with a common approach in the field's literature (Wang *et al.*, 2018; Huang *et al.*, 2015; Antle, 2010; Di Falco and Chavas, 2006), our empirical approach models pesticides as a conventional productive input rather than a damage-abatement input (Lichtenberg and Zilberman, 1986). While this approach enables higher moments of the probability distribution of outcomes to be modelled straightforwardly and to disentangle the partial-moments, it is not without consequences. In particular, it may bias upward the estimated productivity of pesticides (Lichtenberg and Zilberman, 1986). In this view, our estimate of pesticide effect in the expected value equations can be considered as un upper bound of the pesticide effect on yield and revenue per hectare. Turning to the study's limitations, one limitation lies in the indicator used to measure pesticide use. Möhring *et al.* (2020b) argue that contrasting conclusions in studies on the risk impact of pesticides can be explained by the different indicators used to measure pesticides, as well as by the types of pesticides considered. We use pesticide expenditure deflated by the producer price index. While this measure can be criticized (e.g. it is an aggregate measure of all pesticides together and is not quantity-based or disaggregated by active ingredients), as discussed in Section 2.4, it is the only reliable measure available in the Italian FADN data. While we acknowledge its limitations, we also believe that it remains a valid measure of pesticide use in apple production since conventional apple producers in Italy are rather homogeneous, typically relying on the same pesticide products. However, we recognize that this weakens the generalizability of our findings to other types of crops or more heterogeneous farming systems. Moreover, we make note that the construction of the synthetic weather variables used to proxy for unobservable factors was based on satellite data. Although this approach—compared to the use of meteorological station data—allows for greater data granularity and a more accurate interpolation with farm coordinates, measurement errors could be an issue. Such errors may lead to either an overestimation or attenuation of the estimated associations presented throughout the manuscript (for a comprehensive review of possible sources of systematic and non-systematic error see Wuepper *et al.*, 2025). Moreover, our study does not include any measures of farmers' risk and time preferences, beliefs, or perceptions related to pesticide use behaviour. This represents an inherent limitation, as behavioural variables are not captured within the FADN dataset. However, we concur with Finger *et al.* (2018) that farmers' risk preferences warrant closer examination, given their crucial role in shaping farm management decisions. Future studies should combine observational and experimental data to explore the behavioural dimension of farmers' decisions and elicit—for example—individual risk aversion coefficients. As farmers' behavioural factors are crucial for understanding farmers' management decisions (Dessart *et al.*, 2019), this understanding could lead to the development of more effective pesticide reduction policies.

Acknowledgements

The authors acknowledge the financial support from the Italian Ministry of the University and the Research for the PRIN project '*SUSRISK—Towards a holistic approach to sustainable risk management in agriculture*'.

Conflicts of interest. None declared.

Funding

None declared.

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Appendix A

We compared different functional forms according to their AIC and BIC values. As Table A1 shows, the Trans log has the highest AIC and BIC, while the linear quadratic and the log linear have lower but similar AIC and BIC. Given the similarity of the values for the two functional forms, we ultimately chose the linear quadratic because our dataset carries some zeros (about 3 per cent of the observations) in the fertilizer variable and adopting a linear log would have meant correcting for these zeros (Falco *et al.*, 2014).

Table A1. AIC and BIC comparison across functional forms.

	AIC	BIC
	Yield	
Linear quadratic	3153.9	4838.6
Trans log	3294.9	4984.9
Linear log	3148.9	4806.9
	Revenue	
Linear quadratic	3081.8	4766.5
Trans log	3174.2	4864.2
Linear log	3069.9	4728.4

Appendix B

Table B1. Estimation results of the yield and revenue models (estimated coefficients for the expected value equation of the linear quadratic production function).

	Yield	Revenue per hectare
Input variables		
Pesticides expenditure	0.211***	0.122***
	(0.049)	(0.040)
Fertilizers	0.123***	0.012
	(0.041)	(0.040)
Labour	0.515***	0.303***
	(0.095)	(0.063)
Pesticide expenditure squared	−0.031	−0.026*
	(0.021)	(0.015)
Fertilizers squared	−0.015**	0.005
	(0.007)	(0.009)
Labour squared	−0.146**	−0.055
	(0.067)	(0.047)
Pesticide expenditure ∗ Fertilizers	−0.005	0.015
	(0.021)	(0.023)
Fertilizers ∗ Labour	0.008	0.001
	(0.030)	(0.019)
Pesticide expenditure ∗ Labour	−0.010	−0.016
	(0.030)	(0.022)
Late Frost 200GDD	−0.087*	0.187***
	(0.052)	(0.063)
Weather variables—Estimated Coefficients		
Heat waves	0.028	−0.005
	(0.039)	(0.035)
Precipitation April–June	0.028	−0.168***
	(0.036)	(0.037)
Precipitation April–June squared	−0.006	0.054***
	(0.015)	(0.019)
Individual fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Control variables	Yes	Yes
Observations	1,383	1,383
F Statistics	11.416*** (df = 13; 1,062)	6.360*** (df = 13; 1,062)

All Models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table B2. Input elasticity estimates and regression coefficients of agricultural output: yield and revenue per hectare (No Late Frost).

	Yield			*Revenue per hectare*		
	Expected value	Other moments		Expected value	Other moments	
	[1] Elasticity at the mean	Estimated coefficients [2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	Estimated coefficients [5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.161***	−0.019	−0.053*	0.129***	−0.036*	−0.044**
	(0.032)	(0.019)	(0.028)	(0.042)	(0.021)	(0.020)
Fertilizers	0.046***	0.018	0.019	0.012	0.029	0.035
	(0.016)	(0.016)	(0.023)	(0.021)	(0.021)	(0.026)
Labour	0.497***	0.043	0.064	0.376***	0.024	0.048
	(0.062)	(0.047)	(0.101)	(0.082)	(0.024)	(0.033)
Weather variables—Estimated Coefficients						
LateFrost 200GDD				*Not included*		
Heat waves	0.036	−0.007	0.01	−0.022	−0.117***	−0.084***
	(0.038)	(0.028)	(0.052)	(0.035)	(0.025)	(0.030)
Precipitation April–June	0.028	0.015	0.041	−0.168***	−0.106***	−0.042
	(0.035)	(0.021)	(0.039)	(0.037)	(0.021)	(0.026)
Precipitation April–June squared	−0.009	−0.011	−0.013	0.060***	0.010	0.009
	(0.015)	(0.014)	(0.023)	(0.019)	(0.015)	(0.015)
Individual fixed effects	Yes	–	–	Yes	–	–
Time fixed effects	Yes	–	–	Yes	–	–
Control variables	Partial	Partial	Partial	Partial	Partial	Partial
Observations	1,383	1,383	661	1,383	1,383	699
F Statistics	12.209***	1.094	0.9182	6.122***	10.34***	4.182***
	(df = 12, 1063)	(df = 6; 1,376)	(df = 6, 655)	(df = 12, 1063)	(df = 6; 1,376)	(df = 6, 693)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table B3. Input elasticity estimates and regression coefficients of agricultural output: yield and revenue per hectare (No Heat waves).

	Yield			*Revenue per hectare*		
	Expected value	Other moments Estimated coefficients		Expected value	Other moments Estimated coefficients	
	[1] Elasticity at the mean	[2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	[5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.162***	−0.022	−0.063**	0.127***	−0.036*	−0.043**
	(0.032)	(0.019)	(0.027)	(0.042)	(0.021)	(0.020)
Fertilizers	0.047***	0.015	0.017	0.006	0.029	0.038
	(0.016)	(0.016)	(0.022)	(0.021)	(0.021)	(0.028)
Labour	0.492***	0.051	0.089	0.392***	0.024	0.046
	(0.062)	(0.045)	(0.094)	(0.082)	(0.024)	(0.033)
Weather variables—Estimated Coefficients						
LateFrost 200GDD	−0.095*	0.106**	0.239***	0.188***	−0.117***	−0.011
	(0.050)	(0.044)	(0.084)	(0.062)	(0.025)	(0.052)
Heat waves	*Not included*					
Precipitation April–June	0.028	0.003	0.010	−0.168***	−0.106***	−0.040
	(0.035)	(0.021)	(0.038)	(0.037)	(0.021)	(0.027)
Precipitation April–June squared	−0.005	−0.010	−0.014	0.054***	0.010	0.008
	(0.015)	(0.014)	(0.023)	(0.019)	(0.015)	(0.015)
Individual fixed effects	Yes	–	–	Yes	–	–
Time fixed effects	Yes	–	–	Yes	–	–
Control variables	Partial	Partial	Partial	Partial	Partial	Partial
Observations	1383	1383	663	1383	1383	704
F Statistics	12.323***	2.052*	2.491	5.829***	10.34***	4.182***
	(df = 12, 1063)	(df = 6; 1,376)	(df = 6, 657)	(df = 12, 1063)	(df = 6; 1,376)	(df = 6, 698)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table B4. Input elasticityestimates and regression coefficients of agricultural output: yield and revenue per hectare (No Rainfall).

	Yield			*Revenue per hectare*		
	Expected value	Other moments Estimated coefficients		Expected value	Other moments Estimated coefficients	
	[1] Elasticity at the mean	[2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	[5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.162***	−0.022	−0.046**	0.120***	−0.036*	−0.038*
	(0.032)	(0.019)	(0.020)	(0.042)	(0.022)	(0.021)
Fertilizers	0.047***	0.016	0.039	0.007	0.024	0.027
	(0.016)	(0.016)	(0.027)	(0.021)	(0.019)	(0.023)
Labour	0.489***	0.052	0.052	0.413***	0.033	0.033
	(0.062)	(0.047)	(0.033)	(0.082)	(0.022)	(0.030)
Weather variables—Estimated Coefficients						
LateFrost 200GDD	−0.088*	0.107**	−0.005	0.200***	−0.060	−0.015
	(0.051)	(0.042)	(0.045)	(0.064)	(0.045)	(0.045)
Heat waves	0.027	−0.012	−0.074***	0.004	−0.111***	−0.055**
	(0.039)	(0.028)	(0.027)	(0.036)	(0.024)	(0.027)
Precipitation April–June			*Not included*			
Precipitation April–June squared						
Individual fixed effects	Yes	–	–	Yes	–	–
Time fixed effects	Yes	–	–	Yes	–	–
Control variables	Partial	Partial	Partial	Partial	Partial	Partial
Observations	1383	1383	704	1383	1383	706
F Statistics	13.458***	2.513**	4.102*	5.282***	7.45***	2.221***
	(df = 11, 1063)	(df = 5; 1,377)	(df = 5, 699)	(df = 11, 1064)	(df = 5; 1,377)	(df = 5, 701)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table B5. Estimation results of the yield and revenue models without weather variables.

	Yield			*Revenue per hectare*		
	Expected value	Other moments Estimated coefficients		Expected value	Other moments Estimated coefficients	
	[1] Elasticity at the mean	[2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	[5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.162***	−0.019	−0.047*	0.121***	−0.043**	−0.045**
	(0.032)	(0.019)	(0.027)	(0.042)	(0.022)	(0.021)
Fertilizers	0.045***	0.020	0.021	0.014	0.022	0.031
	(0.016)	(0.016)	(0.024)	(0.021)	(0.019)	(0.025)
Labour	0.496***	0.041	0.054	0.395***	0.051**	0.041
	(0.061)	(0.045)	(0.092)	(0.082)	(0.023)	(0.029)
Individual fixed effects	Yes	–	–	Yes	–	–
Time fixed effects	Yes	–	–	Yes	–	–
Control variables	No	No	No	No	No	No
Observations	1,383	1,383	662	1,383	1,383	708
F Statistics	16.125***	1.925	1.388	5.296***	3.04**	2.606*
	(df = 9, 1066)	(df = 3, 1,379)	(df = 3, 658)	(df = 9, 1066)	(df = 3, 1,379)	(df = 3, 704)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table B6. Inputelasticity estimates and regression coefficients of agricultural output: yield and revenue per hectare (estimated without FE).

	Yield			*Revenue per hectare*		
	Expected value	Other moments Estimated coefficients		Expected value	Other moments Estimated coefficients	
	[1] Elasticity at the mean	[2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	[5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.276***	0.046	−0.026	0.299***	0.013	0.006
	(0.025)	(0.076)	(0.027)	(0.032)	(0.049)	(0.020)
Fertilizers	0.064***	0.030	0.080	0.089***	0.08	0.038
	(0.014)	(0.039)	(0.056)	(0.018)	(0.032)	(0.029)
Labour	0.268***	0.199***	0.179***	0.377***	0.118***	0.183***
	(0.029)	(0.071)	(0.052)	(0.037)	(0.041)	(0.039)
Weather variables—Estimated Coefficients						
LateFrost 200GDD	−0.264***	0.136*	0.133*	−0.172***	−0.014	−0.031
	(0.055)	(0.076)	(0.078)	(0.025)	(0.079)	(0.043)
Heat waves	0.070**	0.052	0.072*	−0.213***	−0.273***	−0.163***
	(0.027)	(0.038)	(0.043)	(0.025)	(0.047)	(0.032)
Precipitation April–June	0.055**	−0.036	−0.091**	−0.171***	−0.258***	−0.149***
	(0.025)	(0.034)	(0.038)	(0.026)	(0.044)	(0.030)
Precipitation April–June squared	−0.048**	−0.013	−0.019	0.040**	0.049**	0.042**
	(0.019)	(0.024)	(0.025)	(0.019)	(0.024)	(0.019)
Individual fixed effects	No	–	–	No	–	–
Time fixed effects	No	–	–	No	–	–
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,383	1,383	707	1,383	1,383	745
F Statistics	27.27***	6.862***	6.03***	41.13***	14.13***	21.61***
	(df = 13, 1369)	(df = 7; 1,375)	(df = 7, 699)	(df = 13, 1369)	(df = 7; 1,375)	(df = 7; 737)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table B7. Input elasticityestimates and regression coefficients of agricultural output: yield and revenue per hectare (estimated without FE and without control variables).

	Yield			*Revenue per hectare*		
	Expected value	Other moments Estimated coefficients		Expected value	Other moments Estimated coefficients	
	[1] Elasticity at the mean	[2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	[5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.287***	0.083	−0.0003	0.282***	−0.017	−0.0003
	(0.025)	(0.090)	(0.029)	(0.034)	(0.051)	(0.017)
Fertilizers	0.055***	0.018	0.093	0.086***	−0.013	0.008
	(0.014)	(0.039)	(0.057)	(0.019)	(0.036)	(0.026)
Labour	0.275***	0.176***	0.168***	0.509***	0.224***	0.238***
	(0.028)	(0.064)	(0.049)	(0.038)	(0.050)	(0.036)
Individual fixed effects	No	–	–	No	–	–
Time fixed effects	No	–	–	No	–	–
Control variables	No	No	No	No	No	No
Observations	1,383	1,383	689	1,383	1,383	795
F Statistics	34.66***	12.52***	9.121***	35.78***	5.779***	37.67***
	(df = 9; 1,373)	(df = 3; 1,379)	(df = 3; 685)	(df = 9; 1,373)	(df = 3; 1,379)	(df = 3; 791)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table B8. Input elasticity estimates and regression coefficients of agricultural output: yield and revenue per hectare (Farm level FE, no time FE, yes weather).

	Yield			*Revenue per hectare*		
	Expected value	Other moments Estimated coefficients		Expected value	Other moments Estimated coefficients	
	[1] Elasticity at the mean	[2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	[5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.167***	−0.024	−0.077***	0.098**	−0.039*	−0.047***
	(0.032)	(0.020)	(0.027)	(0.043)	(0.022)	(0.017)
Fertilizers	0.051***	0.012	0.022	0.032	0.028	0.034
	(0.016)	(0.016)	(0.025)	(0.022)	(0.022)	(0.026)
Labour	0.493***	0.053	0.086	0.371***	0.029	0.060*
	(0.062)	(0.049)	(0.103)	(0.085)	(0.026)	(0.033)
Weather variables—Estimated Coefficients						
LateFrost 200GDD	−0.214***	0.115**	0.273***	0.003	−0.034	−0.027
	(0.044)	(0.045)	(0.085)	(0.047)	(0.047)	(0.054)
Heat waves	0.089***	−0.009	−0.001	−0.186***	−0.123***	−0.059**
	(0.025)	(0.028)	(0.052)	(0.021)	(0.027)	(0.029)
Precipitation April–June	0.032	0.005	0.001	−0.216***	−0.110***	−0.026
	(0.023)	(0.022)	(0.040)	(0.026)	(0.024)	(0.028)
Precipitation April–June squared	−0.015	−0.009	−0.018	0.090***	0.008	0.001
	(0.015)	(0.014)	(0.022)	(0.019)	(0.015)	(0.013)
Individual fixed effects	Yes	–	–	Yes	–	–
Time fixed effects	No	–	–	No	–	–
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,383	1,383	670	1,383	1,383	720
F Statistics	14.612***	1.774*	2.409**	16.651***	9.064***	3.277**
	(df = 13; 1,067)	(df = 7; 1,375)	(df = 7; 662)	(df = 13; 1,067)	(df = 7; 1,375)	(df = 7; 712)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table B9. Input elasticity estimates and regression coefficients of agricultural output: yield and revenue per hectare (No individual FE, Yes time FE).

	Yield			*Revenue per hectare*		
	Expected value	Other moments Estimated coefficients		Expected value	Other moments Estimated coefficients	
	[1] Elasticity at the mean	[2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	[5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.247***	0.045	−0.015	0.274***	0.018	0.010
	(0.027)	(0.067)	(0.026)	(0.037)	(0.048)	(0.023)
Fertilizers	0.047***	0.024	0.077	0.097***	0.016	0.041
	(0.027)	(0.039)	(0.056)	(0.024)	(0.031)	(0.029)
Labour	0.176***	0.192***	0.173***	0.254***	0.111***	0.178***
	(0.034)	(0.068)	(0.053)	(0.046)	(0.040)	(0.042)
Weather variables—Estimated Coefficients						
LateFrost 200GDD	−0.181***	0.155**	0.164**	−0.181***	−0.005	−0.065
	(0.069)	(0.073)	(0.076)	(0.067)	(0.076)	(0.044)
Heat waves	−0.023	0.035	0.04	−0.145***	−0.273***	−0.188***
	(0.041)	(0.037)	(0.040)	(0.038)	(0.044)	(0.035)
Precipitation April–June	0.052	−0.039	−0.078**	−0.155***	−0.248***	−0.142***
	(0.041)	(0.033)	(0.038)	(0.030)	(0.042)	(0.032)
Precipitation April–June squared	−0.033	−0.013	−0.023	0.029	0.036	0.039*
	(0.023)	(0.023)	(0.025)	(0.020)	(0.024)	(0.020)
Individual fixed effects	No	–	–	No	–	–
Time fixed effects	Yes	–	–	Yes	–	–
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,383	1,383	701	1,383	1,383	745
F Statistics	25.023***	6.808***	5.369***	32.860***	14.95***	20.48***
	(df = 13; 1364)	(df = 7; 1,375)	(df = 7; 693)	(df = 13; 1364)	(df = 7; 1,375)	(df = 7; 737)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table B10. Inputelasticity estimates and regression coefficients of agricultural output: yield and revenue per hectare (No individual FE, Yes time, no weather control).

	Yield			*Revenue per hectare*		
	Expected value	Other moments Estimated coefficients		Expected value	Other moments Estimated coefficients	
	[1] Elasticity at the mean	[2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	[5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.268***	0.061	0.009	0.254***	−0.006	0.002
	(0.027)	(0.069)	(0.028)	(0.038)	(0.051)	(0.027)
Fertilizers	0.035**	0.029	0.078	0.101***	0.012	0.024
	(0.017)	(0.039)	(0.055)	(0.024)	(0.032)	(0.031)
Labour	0.186***	0.177***	0.158***	0.312***	0.175***	0.215***
	(0.034)	(0.063)	(0.049)	(0.049)	(0.043)	(0.046)
Individual fixed effects	No	–	–	No	–	–
Time fixed effects	Yes	–	–	Yes	–	–
Control variables	No	No	No	No	No	No
Observations	1383	1383	699	1383	1383	740
F Statistics	34.60***	13.46***	8.957***	40.74***	5.663***	19.26***
	(df = 9; 1,368)	(df = 3; 1,379)	(df = 3; 696)	(df = 9; 1,369)	(df = 3; 1,379)	(df = 3; 737)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table B11. Inputelasticity estimates and regression coefficients of agricultural output: yield and revenue per hectare (Farm FE, No time FE, no weather control).

	Yield			*Revenue per hectare*		
	Expected value	Other moments Estimated coefficients		Expected value	Other moments Estimated coefficients	
	[1] Elasticity at the mean	[2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	[5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.181***	−0.016	−0.067**	0.045	−0.037	−0.017
	(0.032)	(0.024)	(0.027)	(0.047)	(0.025)	(0.018)
Fertilizers	0.033**	0.011	0.021	0.041	0.001	0.021
	(0.016)	(0.016)	(0.026)	(0.023)	(0.021)	(0.021)
Labour	0.525***	0.033	0.044	0.372***	0.103***	0.081***
	(0.063)	(0.042)	(0.083)	(0.091)	(0.030)	(0.031)
Individual fixed effects	No	–	–	No	–	–
Time fixed effects	Yes	–	–	Yes	–	–
Control variables	No	No	No	No	No	No
Observations	1383	1383	679	1383	1383	739
F Statistics	16.623***	0.9778	1.583	3.384***	4.407***	4.477***
	(df = 9; 1,071)	(df = 3; 1,379)	(df = 3; 676)	(df = 9; 1,071)	(df = 3; 1,379)	(df = 3; 736)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table B12. Inputelasticity estimates and regression coefficients of agricultural output: yield and revenue per hectare (Agrarian region FE, Yes time FE, Yes weather control).

	Yield			*Revenue per hectare*		
	Expected value	Other moments Estimated coefficients		Expected value	Other moments Estimated coefficients	
	[1] Elasticity at the mean	[2] Variance	[3] Negative semi-variance	[4] Elasticity at the mean	[5] Variance	[6] Negative semi-variance
Input variables						
Pesticides expenditure	0.242***	−0.020	−0.064***	0.258***	−0.047	−0.045**
	(0.025)	(0.030)	(0.024)	(0.031)	(0.032)	(0.019)
Fertilizers	0.058***	0.010	−0.007	0.072***	0.020	0.076**
	(0.013)	(0.037)	(0.027)	(0.017)	(0.029)	(0.031)
Labour	0.095**	0.101**	0.124*	0.122**	0.078**	0.077**
	(0.036)	(0.044)	(0.069)	(0.045)	(0.034)	(0.033)
Weather variables—Estimated Coefficients						
LateFrost 200GDD	−0.070	0.138**	0.230***	0.146**	0.031	−0.016
	(0.065)	(0.057)	(0.075)	(0.057)	(0.071)	(0.041)
Heat waves	0.049	0.013	0.018	0.011	−0.169***	−0.120***
	(0.041)	(0.034)	(0.045)	(0.033)	(0.034)	(0.033)
Precipitation April–June	0.004	−0.018	−0.059*	−0.153***	−0.166***	−0.101***
	(0.037)	(0.027)	(0.030)	(0.040)	(0.031)	(0.026)
Precipitation April–June squared	0.005	−0.025	−0.054***	0.054***	−0.0001	0.017
	(0.019)	(0.020)	(0.020)	(0.018)	(0.021)	(0.018)
Agrarian region fixed effects	Yes	–	–	Yes	–	–
Time fixed effects	Yes	–	–	Yes	–	–
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1383	1383	707	1383	1383	724
F Statistics	14.21***	2.712**	3.56**	20.71***	9.989***	9.733***
	(df = 57, 1325)	(df = 7, 1375)	(df = 7, 700)	(df = 57, 1325)	(df = 7, 1375)	(df = 7, 717)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Appendix C

We consider a 13 × 13 grid of 169 equally spaced correlation values for $\rho_{Y\sim Z|X,D}$ and $\rho_{D\sim Z|X}$, ranging from -0.6 to $+\,0.6$. For each point on the grid, we draw 200 different vectors Z, each yielding that many new pesticide expenditure elasticities which are eventually averaged to produce the marginal effect under violated OVB.

Figure C1 shows the sensitivity analysis results for the pesticide expenditure elasticity in the mean equation for the yield outcome (left panel) and the per-hectare revenue outcome (right panel), respectively. The numbers in each cell indicate the estimated elasticity under the simulated confounder conditions identified by the corresponding combination of $\rho_{Y\sim Z|X,D}$ and $\rho_{D\sim Z|X}$ values.

First, notice that when either one of the correlations is equal to zero, the elasticity of interest is uncounfounded as OVB requires that either $\rho_{Y\sim Z|X,D}$ or $\rho_{D\sim Z|X}$ are different from zero. However, when Z positively (negatively) correlates with both the yield outcome and pesticide expenditure, the elasticity for the latter approaches zero at approximately $|\rho_{Y\sim Z|X,D}| \approx |0.4|$ and $\rho_{D\sim Z|X} \approx 0,75\rho_{Y\sim Z|X,D}$. Larger correlation values flip the corresponding elasticity sign from positive to negative. Conversely, when the partial correlations pull in different directions, the parameter size gets amplified, although at lower association values the differences remain contained. When switching to the revenue per-hectare outcome, the pesticide elasticities are, in this case, more sensitive to OVB. In particular, the elasticity approaches zero for smaller correlations between Z and the observed revenue, i.e. $|\rho_{Y\sim Z|X,D}| \approx |0.1|$, but for much larger correlations between Z and D, i.e. $\rho_{D\sim Z|X} \approx 5\rho_{Y\sim Z|X,D}$ ($\rho_{D\sim Z|X} \approx 0.5$).

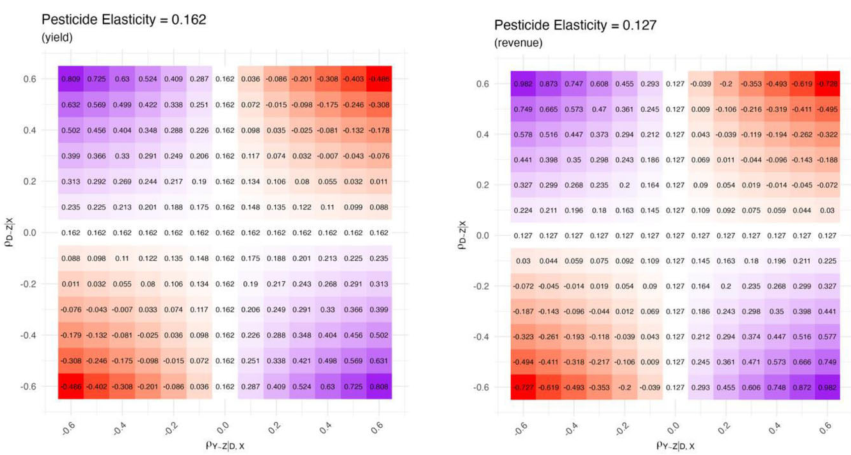

Figure C1. Sensitivity analysis results for the expected value equation.
Note: The left (right) panel represents the estimated pesticide expenditure elasticities under different combinations of $\rho_{Y\sim Z|X,D} \in (-0.6, 0.6)$ and $\rho_{D\sim Z|X} \in (-0.6, 0.6)$ for the yield (per-hectare revenue) outcome.

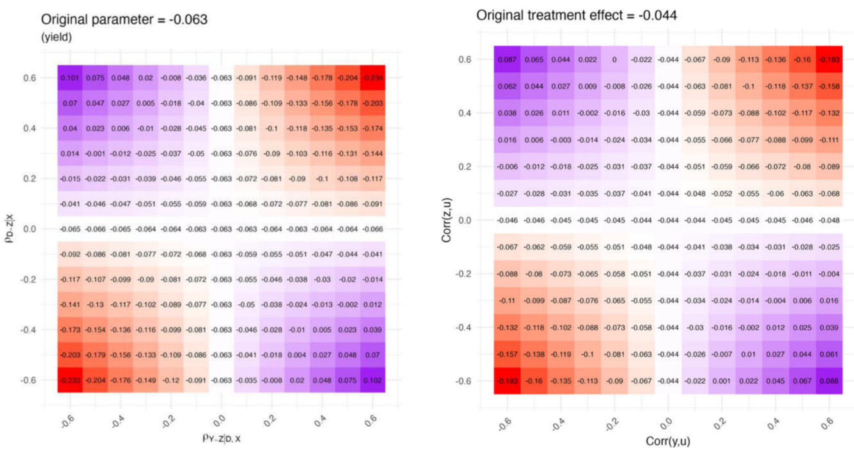

Figure C2. Sensitivity analysis results for the negative semi-variance equation.
Note: The left (right) panel represents the estimated pesticide expenditure under different combinations of $\rho_{Y\sim Z|X,D} \in (-0.6, 0.6)$ and $\rho_{D\sim Z|X} \in (-0.6, 0.6)$ for the yield (per-hectare revenue) outcome.

Figure C2 shows how the pesticide expenditure coefficient changes across different correlation levels in the negative semi-variance equation for both the yield outcome (left panel) and the per-hectare revenue outcome (right panel). Unlike the previous cases, the estimated parameters change in sign for diverging partial correlations, larger while positive (negative) values of $\rho_{Y\sim Z|X,D}$ and $\rho_{D\sim Z|X}$ yield more negative coefficients. In particular, the coefficient for pesticide expenditure roughly vanishes for $\rho_{Y\sim Z|X,D} = \pm 0.4$ and $\rho_{D\sim Z|X} = -\rho_{Y\sim Z|X,D}$ for both the yield and the per-hectare revenue model.

Overall, this second sensitivity analysis roughly aligns with the one discussed at the beginning of Section 4.4. Specifically, we find that the pesticide expenditure parameters in Equation (4) appear robust to moderate correlations between the outcome and the corresponding treatment variable, after controlling for other covariates, when yield is considered. The revenue equation, on the other hand, appears slightly less robust, as lower value of partial correlation between the confounder and the outcome variables are sufficient to shrink the elasticity towards zero. However, results for the negative semi-variance equations indicate that these models are approximately as robust to OVB.

Appendix D

Table D1. Placebo outcome test: yield and revenue per hectare for other crops on pesticide expenditure for apples.

	Yield for other crops		*Revenue per hectare for other crops*	
	Expected value	Negative semi-variance	Expected value	Negative semi-variance
	Elasticity at the mean	Estimated coefficients	Elasticity at the mean	Estimated coefficients
Input variables				
Pesticides expenditure	0.639*	−0.046	0.066	−0.001
	(0.333)	(0.029)	(0.068)	(0.018)
Fertilizers	−0.213	0.099	−0.027**	−0.003
	(0.168)	(0.108)	(0.034)	(0.014)
Labour	−1.263***	0.151	0.252	0.008
	(0.646)	(0.111)	(0.132)*	(0.015)
Weather variables—Estimated Coefficients				
LateFrost 200GDD	−0.055	0.183	0.022	−0.035
	(0.058)	(0.126)	(0.045)	(0.058)
Heat waves	−0.014	0.054	−0.017	0.093***
	(0.027)	(0.048)	(0.025)	(0.027)
Precipitation April–June	0.002	0.07	−0.038	0.007
	(0.031)	(0.045)	(0.027)	(0.024)
Precipitation April–June squared	−0.010*	0.017	−0.026*	0.011
	(0.006)	(0.045)	(0.014)	(0.017)
Individual fixed effects	Yes	–	Yes	–
Time fixed effects	Yes	–	Yes	–
Control variables	Yes	Yes	Yes	Yes
Observations	1383	713	1383	675
F Statistics	2.255***	2.4965	1.934**	2.055*
	(df = 13; 1,062)	(df = 7; 706)	(df = 13; 1,062)	(df = 7; 668)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.

Table D2. Placebo treatment test: yield and revenue per hectare on pesticide expenditure for other crops.

	Yield		*Revenue per hectare*	
	Expected value	Negative semi-variance	Expected value	Negative semi-variance
	Elasticity at the mean	Estimated coefficients	Elasticity at the mean	Estimated coefficients
Input variables				
Pesticides expenditure for other crops	0.007	−0.089***	−0.019	−0.083***
	(0.019)	(0.029)	(0.011)	(0.018)
Fertilizers	0.044***	0.011	0.005	0.029
	(0.016)	(0.022)	(0.021)	(0.024)
Labour	0.476***	0.007	0.394***	0.022
	(0.061)	(0.034)	(0.082)	(0.024)
Weather variables—Estimated Coefficients				
LateFrost 200GDD	−0.090*	0.238***	0.112***	0.036
	(0.051)	(0.079)	(0.023)	(0.051)
Heat waves	0.027	−0.015	−0.002	−0.085***
	(0.039)	(0.037)	(0.036)	(0.027)
Precipitation April–June	0.02	−0.015	−0.115***	−0.062**
	(0.036)	(0.037)	(0.023)	(0.029)
Precipitation April–June squared	−0.006	−0.006	0.015	0.02
	(0.015)	(0.022)	(0.019)	(0.015)
Individual fixed effects	Yes	–	Yes	–
Time fixed effects	Yes	–	Yes	–
Control variables	Yes	Yes	Yes	Yes
Observations	1383	652	1383	705
F Statistics	10.370***	2.404*	5.670***	4.554***
	(df = 18; 1,059)	(df = 8; 650)	(df = 18; 1,059)	(df = 7; 698)

All models are estimated on standardized data.
Heteroskedasticity-robust standard errors in parenthesis.
*, ** and *** indicate significance at 10, 5 and 1 per cent level.