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Comparative Analysis of Organic Farming in the EU: Implications for Crop Protection Costs, Labour, and Income.

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Abstract

The European Union (EU) aims to increase the adoption of organic farming as part of its Farm to Fork Strategy. However, farmers face various adoption hurdles, such as the efficacy of crop protection, as well as implications for crop yields, costs, labour and ultimately farm income. Yet, we currently lack comprehensive large-scale empirical evidence on the economics of organic farming in the EU. Therefore, this study assesses the economic performance of organic farming in the EU using a large-scale cross-country dataset. It consists of an unbalanced panel of 151,560 non-organic and 10,531 organic farms from the European Farm Accountancy Data Network, covering seven different farm types and 16 EU countries. Our analysis specifically focuses on crop protection expenditures, total crop specific costs, as well as labour and gross farm income on a per hectare basis. We find that organic farming adoption significantly reduces crop protection expenditures as well as total crop specific costs across all farming types. Differences in farm-level labour inputs between organic and non-organic farms turned out to be only minor. Farm income is smaller for organic farms without subsidies but higher when accounting for subsidies. However, all effects are highly heterogeneous across farm types and across space. Our study contributes to a better understanding of the economic implications of organic farming within the EU. These insights can inform both practitioners and policy decision-makers and facilitate the achievement of regional organic farming targets.

JEL Codes: O570; O330; Q120.

1. INTRODUCTION

The agricultural and food sector is linked to a range of detrimental environmental effects, including water pollution, biodiversity loss, and climate change (Dudley & Alexander, 2017; FAO, 2017; Lynch et al., 2021). Reducing these negative impacts while maintaining productivity levels and ensuring food security is one of the key challenges faced by all actors in the food system (Pretty et al., 2018). Organic farming is one element in reaching these goals, and especially the European Union (EU) emphasizes this pathway and aims to expand organic farming (Moschitz et al., 2021; Schebesta & Candel, 2020). The adoption of organic farming carries economic implications for farm profitability, affecting input costs, labour demand as well as yields, revenues, prices and subsidies (Crowder & Reganold, 2015; Orsini et al., 2018a). While effects vary across crops and regions, organic farming is often perceived as having higher production costs (Post & Schahczenski, 2012) and increased production risks (Knapp et al., 2018; Tzouramani et al., 2008), largely due to potential inefficiencies in crop protection (Deguine & Penvern, 2014a; Litterick et al., 2002) and other restrictions such as the non-use of mineral fertilizer. Concerns about potential decline in productivity and profitability associated with non-chemical pest control practices (Bakker, Sok, Van Der Werf, et al., 2021) significantly influence farmers' decisions regarding adoption[1] (Chèze et al., 2020; Dessart et al., 2019). Currently only 9.9% of agricultural land in the EU managed organically (Willer et al., 2022). Understanding the economic effects of adopting organic farming, particularly in relation to crop protection, is paramount for dispelling common myths that may hinder adoption and guiding policy decisions. This is especially crucial given the objectives outlined in the Farm to Fork Strategy, aiming to elevate organic production to 25% of EU agricultural land by 2030, while reducing the use and risk of chemical pesticides and the use of more hazardous[2] pesticides by 50% by 2030. (Burtscher-Schaden et al., 2022; Finger, 2024)[3].

This study provides a comprehensive cross-country assessment of the farm-level economic effects of adopting organic farming in the EU, using farm-level data from the Farm Accountancy Data Network (FADN) covering 7 farm types and 16 countries over the period 2013-2019. In total we use data from 162,091 farms, 151,560 non-organic and 10,531 organic. More specifically, we analyse economic performance indicators directly linked with the implementation of organic farming, such as crop protection expenditures per hectare, total crop specific input costs, labour inputs (both total and family

[1] Farmers adoption behaviour of organic farming is affected by various interrelated factors, such as technological lock-in (Hammond Wagner et al., 2016), market demand, and behavioural aspects like preferences and social norms (Möhring & Finger, 2022a; Mzoughi, 2020a).

[2] In the Farm to Fork strategy, a clear definition is lacking for the term 'hazardous,' which is often used without specificity despite the existence of objective assessment criteria for gauging its impact on humans and the environment.

[3] See for example Barreiro-Hurle (2022), Wesseler (2022) and Finger (2024) for critical reflections on the Farm-to-Fork strategy and related goals (Barreiro-Hurle et al., 2022; Finger, 2024; Wesseler, 2022).

specific) per hectare, and gross farm income (both with and without subsidies) per hectare. We employ the inverse probability weights regression adjustment estimator to mitigate potential bias arising from observable factors, such as the self-selection of organic farms. Furthermore, we test for potential omitted variable bias following (Diegert et al., 2023). Additionally, we conduct a heterogeneity analysis to examine whether the effects of adopting organic practices on various economic indicators vary based on farm size and region.

Our study contributes to the existing literature in two significant ways. Firstly, it offers a comprehensive evaluation of the impacts of transitioning to organic farming on input costs, labour inputs, and income indicators. We here contribute by providing large scale evidence for 7 farm types and 16 countries in the EU. This addresses a gap left by studies that often focus on specific regions, farm types, or crops, thereby lacking broader comparability and applicability and failing to capture the diverse agricultural landscape of the EU, including for e.g. environmental conditions, farm structures, and systems. Additionally, it extends beyond global meta-studies, such as Crowder and Reganold (2015), by adding detailed insights specific to farm-level effects and farming types within the EU context. Secondly, we here leverage a large dataset to overcome the limitations associated with small sample sizes and to integrate the heterogeneity across farms, farm types and regions within the EU. By doing so, the study will feed the current political debate on the farm-level implications of the promotion of organic agriculture in the EU and contribute to the ongoing debate on the farm-level economic consequences associated with the implementation of the Farm to Fork Strategy.

The rest of the paper unfolds as follows. Section 2 provides an overview of the economic aspects related to organic and non-organic crop protection. Section 3 describes the empirical strategy and the data. Section 4 presents the main results, including the outputs of the sensitivity to omitted variable bias. Section 5 discusses the results while conclusions and policy implications are outlined in the final section.

2. BACKGROUND

2.1. Conceptual Framework

To undertake a sound comparative analysis of the economics of organic crop protection, we build our conceptual framework based on previous literature describing organic crop protection (Deguine & Penvern, 2014b; Letourneau & Bruggen, 2006) and the large number of studies that addressed the productivity and profitability of organic farming (e.g. (Ponisio et al., 2015; Seufert, 2019; Uematsu & Mishra, 2012). Figure 1 provides an overview of the factors influencing the economics of organic and non-organic crop protection.

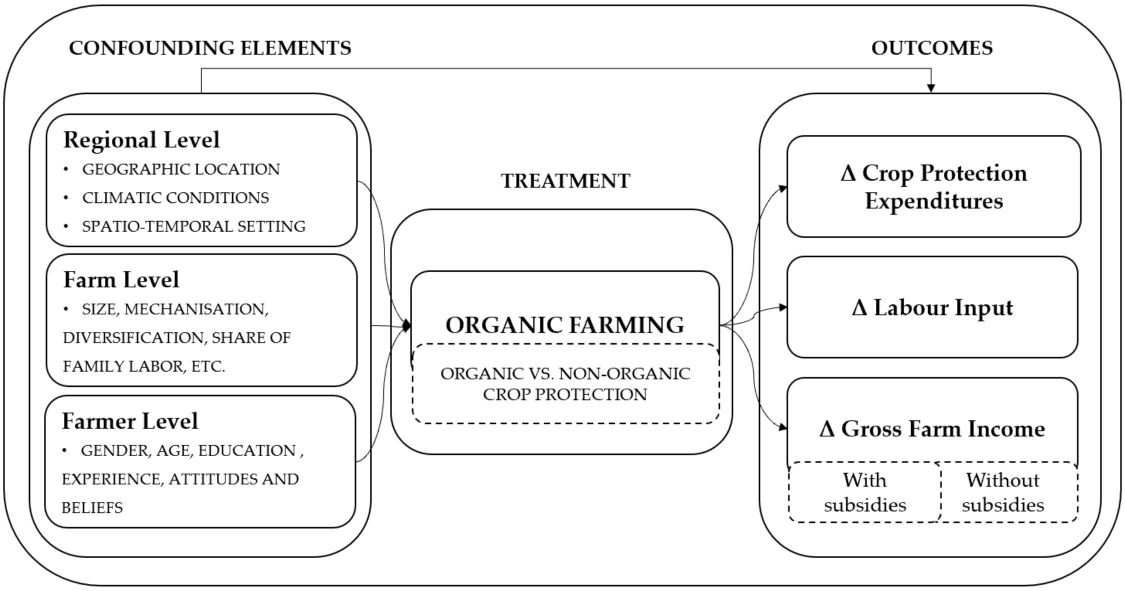

Figure 1.Visualising the economics of organic crop protection. Source: own elaboration.

Non-Organic and Organic Crop Protection Strategies

Understanding how weeds, pests and diseases are managed on organic farms compared to non-organic farms is essential to undertake a sound analysis on the economics of organic crop protection. The main difference lies in the fact that organic farmers are not allowed to use most of the synthetic plant protection substances that non-organic farmers can rely on (EC regulation No 889/2008). Figure 2 shows crop protection management strategies on organic and non-organic farms. Organic growers rely on combinations of alternative strategies, including the use of preventive measures, self-regulation processes and curative non-chemical treatments. Organic crop protection usually is more knowledge-intensive and relies on a system-based approach. Curative non-chemical treatments, including for instance the application of biopesticides, should only be taken as a last measure when pest populations begin to rise, complementing the other approaches (Letourneau & Bruggen, 2006). Copper and mineral oils are among the most widely used plant protection products by organic European farmers[4] (Varga et al., 2022).

It is important to note that crop protection practices are not mutually exclusive between organic and non-organic farming systems. For instance, the use of bio-pesticides such as copper, is not exclusive to organic farms (Torre, 2023). Moreover, as Figure 2 illustrates, both systems exhibit varying levels of

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[4] Organic pesticides, while considered less harmful than synthetic pesticides, still carry environmental risks. For instance, a study conducted by Bahlai et. al. (2010) on the use of organic plant protection products concluded that the latter may not effectively mitigate environmental risk when compared with synthetic products.

input use intensity and integration of practices. There are organic farms that use simple substitution of products and there are organic farms that rely more on alternatives (either ecological or physical or both). Conventional farms may only use synthetic pesticides or revert to integrated pest management to varying degrees. This variation in terms of crop protection practices within systems is documented in different studies (e.g. Deguine & Penvern, 2014; Montalba et al., 2019). For example, some organic farms may focus more on substituting chemical synthetic pesticides with alternative products, while others may prioritize approaches that redesign farming systems to minimize pest pressure. (see e.g.(Deguine et al., 2023; Finger, 2021; Möhring & Finger, 2022b). In summary, the boundaries between organic and non-organic farming systems are not rigid when it comes to crop protection practices. Both systems exhibit diverse levels of input use and embrace various strategies, with practices overlapping between them.

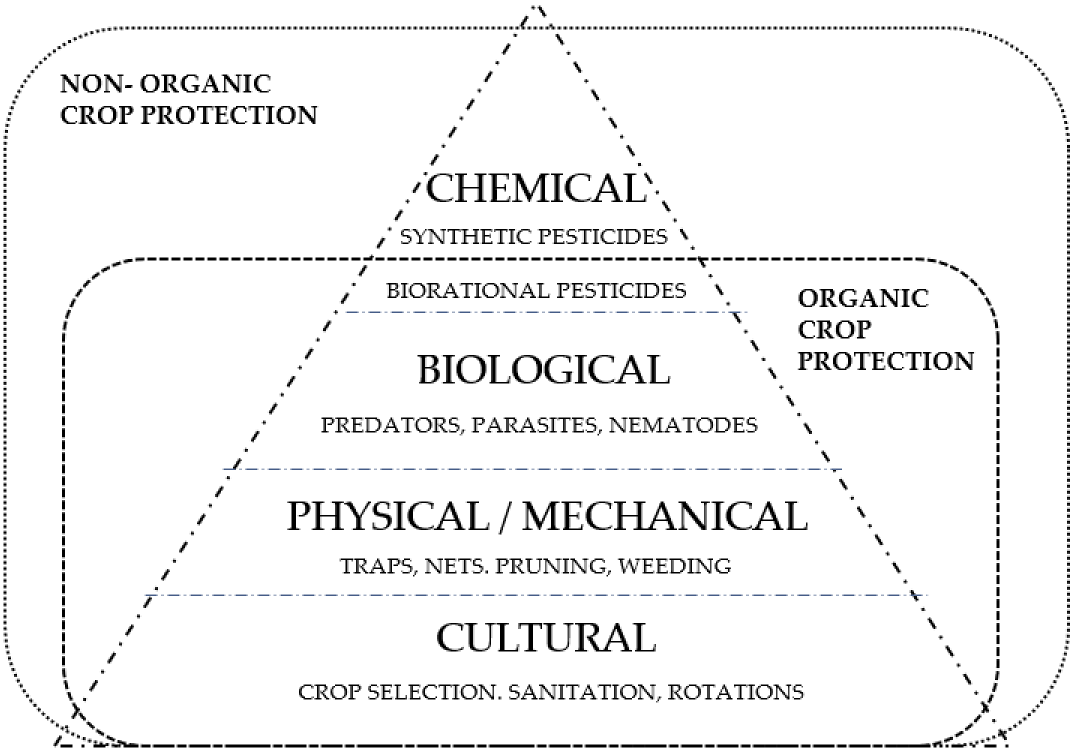


Figure 2. Crop protection management strategies on organic and non-organic farms. Modified from https://www.epa.gov/ipm/definition-verifiable-school-ipm.

Importantly, the choice of crop protection strategy depends on many factors, but mainly the type of crops grown on the farm and the pest threats (Nicholson & Williams, 2021). Of course, these change across climatic zones and therefore geographic regions (as shown in Figure 1). In particular, the application intensity of synthetic inputs varies by crop type and region. Globally, the largest share of pesticides is used on cereal crops, followed by fruits and vegetables. Regional variations in the use of pesticide are also visible across EU countries (EEA, 2022).

Crop Protection: Expenditures and Return on Expenditures

Organic crop protection practices strongly influence the economic performance of organic farms. Generally, crop protection expenditures are relatively low compared to crop sales prices and total production costs. The average share of crop protection expenditures relative to the total input costs ranges around 7-8 %, with variations among farming types and geographical regions (Popp, 2011; Popp et al., 2013). On organic farms, input costs, including expenses for plant protection products, are typically lower compared to conventional farms (Crowder & Reganold, 2015). However, the impact of adopting organic farming on total crop protection expenditures can vary based on the extent and manner in which synthetic inputs are substituted, as well as the prices of the substitute inputs. For example, a study examining the economics of strawberry production found that organic farms incurred higher crop protection costs due to the increased expense of alternative inputs (Bolda et al., 2019). The returns on crop protection expenditures can fluctuate based on several factors, including crop type, specific regions, farming practices, weather conditions, and the effectiveness of crop protection measures employed (e.g. (Horowitz & Lichtenberg, 1994).

Labor Input

Labor input and cost on a farm can vary due to a variety of factors, including the specific crop protection strategies employed. Among these factors, the choice of crop protection methods has a notable impact on labor requirements and associated costs. For instance, in conventional farming, synthetic pesticides are typically applied using mechanized techniques, reducing labor requirements. In contrast, alternative methods used in organic farming like biological control and manual weed removal, are more labor-intensive. Previous studies have indicated that organic farms often have higher labor requirements and costs (Jansen, 2000), primarily due to the allocation of more resources to mechanical weed control (Orsini et al., 2018b). Furthermore, according to Spruijt-Verkerke et al. (2004), labor intensity may be higher in organic farming due to the increased frequency of treatments required when employing organic crop protection methods. However, the rise in labor demand may also stem from the greater diversity of enterprises or the necessity to develop new marketing and processing activities (Ricker, 1997). Some findings are ambiguous and significant variations in labor input were observed across different farming types and regions. For example, labor usage per hectare was found to be higher on organic arable farms and vineyards but lower on olive farms (Offermann & Nieberg, 2000). Studies examining vegetable and mixed farms yielded mixed effects (Orsini et al., 2018b). Furthermore, some studies suggest that the increased labor requirements on organic farms are fulfilled through alternative forms of unpaid labor (Avital, 2019).

Crop Yields, Prices and Subsidies

Difficulties with weed control (McBride et al., 2015) and inadequate pest management (Seufert, 2019), including the lower effectiveness of non-chemical pesticide management strategies (Deguine & Penvern, 2014b), are some of the main reasons for the lower yields observed in organic farming (Seufert, 2019). Various studies investigated the yield implications of organic farming (Seufert, 2019) and the implications that expanding the area under organic farming might have on the food system at large (Muller et al., 2017). Recent meta-analyses with global coverage showed that organic crop yields are on average around 80% of conventional yields (De Ponti et al., 2012; Ponisio et al., 2015). Nevertheless, yield differences are very variable across regions and crop types. For instance, in the case of leguminous crops a yield gap of only 5% was found between organic and non-organic production systems (Ponisio et al., 2015; Wilbois & Schmidt, 2019). Moreover, the extent of the gap is largely dependent on the context and the way in which organic farming is implemented (Schader et al., 2021; Seufert, 2019). Other studies looked specifically at the associations between yields and pesticide use reduction. Hossard et al. (2014) estimated a yield loss of around 15% in wheat production across France as a result of halving pesticide use (Hossard et al., 2014; Lechenet et al., 2017). On the contrary, Lechenet et al. 2017 found no trade-off between reduced pesticide use and productivity or profitability on arable production in France (Lechenet et al., 2017). Importantly, production risks also differ among organic and non-organic farms. Knapp et al. (2018) showed through a meta-analysis of 193 studies that organic farming has, per unit yield, a significantly lower temporal stability compared to conventional agriculture. Similarly, another meta-analysis highlighted variable outcomes in terms of yield stability on organic vs. non-organic farms (Seufert & Ramankutty, 2017).

When comparing certified organic and non-organic farms, it should be noted that the former generally receive premium prices for their products (Bellassen et al., 2022). Despite potentially lower yields, these premium prices can contribute to better economic outcomes for organic farms (Crowder & Reganold, 2015). Additionally, subsidies play a significant role in the economics of organic and non-organic farming. Organic farms generally have access to a broader range of subsidies compared to non-organic farms. For instance, under the 2014-2022 Common Agricultural Policy, organic farmers are complying with the requirements to access the direct payments scheme linked with the implementation of greening measures (EC, 2014). Generally, the share subsidies is higher on organic farms in most EU member states. (EC, 2013).

Other factors influencing the performance of organic vs. non-organic crop protection

A valid comparative analysis of the economics of organic and non-organic crop protection must account for all confounding elements that influence our outcomes of interest. Based on previous literature (e.g. Mzoughi, 2020; Nicholson & Williams, 2021; Świtek et al., 2022), we identified three main categories of confounding elements: i) the spatial and temporal setting ; ii) the farm characteristics; iii) and the farmer characteristics.

The spatial setting of the farm is an important variable to control for since it determines a wide set of interrelated environmental and socio-economic variables (e.g. climate, pest pressure, cultural norms, as well as input and output prices) associated with crop protection costs and productivity. Importantly, the location of conventional and organic crop farmers does not differ significantly in developed countries (Malek et al., 2019), suggesting that differences in the location of organic vs. non-organic should not be a factor of bias. The temporal frame must also be controlled for when using time series data since changes in climate and pest pressure might occur over time. Farm structural characteristics, such as farm size, the degree of mechanization, the level of diversification also influence the economics of organic crop protection. For instance, a study by Świtek et al. (2022) found a positive association between farm size and crop protection costs. Several studies also documented the effects of diversification on pest pressure and yields (e.g.(Stefan et al., 2021). In particular, the practices of multi-cropping and crop rotations[5], were found to substantially reduce the yield gap between organic and non-organic farms (Ponisio et al., 2015). Other factors, such as having crop insurances, also affect the extent of pesticide use (Li et al., 2022). Finally, farmers' characteristics, such as age, education level, farming experience as well as attitudes and believes are also associated with the adoption of organic farming and the implementation pesticide reduction strategies (Möhring & Finger, 2022b). Especially risk attitudes and adoption behaviors of neighboring farmers, play an important role in this regard (Bakker, Sok, van der Werf, et al., 2021; Lapple & Kelley, 2015; Wang et al., 2023).

3. EMPIRICAL FRAMEWORK AND DATA

The main goal of our analysis is to quantify the effect of implementing organic farming, our treatment variable, on crop protection expenditures and other economic performance indicators linked to crop protection (see Annex, Table A1 for the description of the indicators included in the analysis). To do so, we use empirical farm level data from a large sample of farms reflecting agronomic realities across the EU over the period 2013-2019. To ensure the reliability of our findings and mitigate the impact of endogeneity, such as selection bias, our study is designed to address these concerns and establish comparability between organic and non-organic producers. We consider the risk of selection bias arising from observable characteristics while also examining the potential for omitted variable bias (see section 3.2). For instance, it is important to consider that larger farms may be more inclined to adopt organic practices, but they also tend to have higher profitability in general. Therefore, a straightforward

[5] Such variables are not to be considered as covariates since they are not independent from treatment status.

comparison between organic and non-organic farms could be biased due to this confounding factor. We here use the inverse probability weighted regression adjustment estimator to account for such potential bias[6], and to compute the Average Treatment Effect for the Population (ATE) for each outcome variable (see e.g. Wuepper et al. 2021). The ATE allows us to estimate the effects for the entire population of farms and thus extends our understanding of the impacts of adopting organic farming to all farms represented by our sample.

3.1.Empirical Model

The inverse probability weighted regression adjustment estimator involves three main steps. First, the probability of each observation to be assigned to a specific treatment given a set of observed covariates is calculated. To estimate the probability of treatment (also called propensity score), we used the following covariates: farm size, rented land, share of income from other gainful activities, altitude and location (see Annex, Table A3 for description of covariates). In a second step, the inverse probability weights are calculated. These are computed as 1/propensity score for the treated group and 1/(1-propensity score) for the untreated group. In a third step, the outcome model is estimated using the weights and the set of covariates described below (see equation 1). This approach provides a doubly robust estimator, as it requires only the treatment or the outcome model to be correctly specified (Bang & Robins, 2005; Kurz, 2022). The weights were then used in the following regression model that was specified separately for each farm type *f*.

$$Y_{i|f} = \beta_0 + w\beta_1 ORG_f + w\beta_2 COV_f + \varepsilon_{inuts2|f} \qquad (1)$$

In the equation, Y represents one of the outcome variables for each farm (indexed by "i"). The inverse probability weight, denoted as "w," is a weight assigned to each observation based on the inverse of the probability of treatment assignment. The treatment variable, denoted as "ORG," is a binary variable that takes the value 1 if the farm is certified with an officially recognized organic standard and 0 otherwise. The coefficient β_1 captures the ATE of adopting organic farming on the outcome variable Y, assuming all other variables are held constant. COV are the set of observable confounders we control for. The coefficient β_2 represents the effect of these covariates on Y, assuming all other variables are constant.

We choose both outcome and explanatory variables in line with the conceptual framework presented in the previous section and based on data availability. The outcome variables include crop protection expenditures (€/ha), total crop specific costs (€/ha), total labour inputs (AWU/ha), total family labour input (FWU/ha), gross farm income with and without subsidies (€/ha) (a description of the variables

[6] We do not use a fixed effects model in our analysis since we have little variation in the panel and given the limitation that unobserved heterogeneity that is time-invariant is not invariant to the length of the panel (Millimet & Bellemare, 2023).

used in the computation of the outcome variables is presented in Annex, Table A1). Among the explanatory variables, structural farm characteristics include farm size in hectares of agricultural land, size of the agricultural land that is rented, altitude, location, year. Soil and climatic conditions are captured through geographic variables such as altitude, location and year.

We use clustered standard errors based on the NUTS2[7] region level to account that observations within these groups are assumed to share similar institutional, economic, and social conditions. Moreover, to control for variables that are constant across entities but vary over time for the EU at large (e.g. accounting for policy shifts, shocks in markets and climatic conditions) we include time fixed effects. We run the regressions separately for each farming type (see section 3.3, Table 1 for the farming type definitions), to ensure a higher degree of comparability between organic and non-organic farms, since cost and revenue structures are more likely similar within the same farming types. The Stata code is provided in the supplementary material.

3.2.Robustness checks

In this study we assess the extent to which our results are sensitive to omitted variable bias. For instance, information on farmers personal characteristics (e.g. attitudes and beliefs) or on crop varieties planted, which might influence the outcomes of interest, are not available in the FADN dataset, thus potentially leading to biased results. To quantify the sensitivity of the results to omitted variables bias, we applied the approach proposed by Diegert, Masten and Priorier (2022) using the regsensitivity package in STATA. This approach allows the included control variables to be endogenous, and compare the magnitude of selection on observables with the magnitude of selection on unobservable. It introduces a model that incorporates observed variables (Y, X, W0, W1) and an omitted variable (W2) that may exhibit correlation with (X, W0, W1). The sensitivity analysis focuses on the variable of interest X, which in our case is the treatment variable ORG. Y is one of our outcome variables. W0 represents the control variables, while W1 denotes the calibration variables. In our case, we use all control variables as calibration variables. For reasons of conciseness, we apply this robustness check to only three indicators.

3.3.Data

We use part of the FADN dataset, collected by the European Commission to undertake a comparative analysis of the economics of crop protection between organic and non-organic farms. This dataset has been increasingly used by researchers to analyze important dynamics and policy impacts within the

[7] The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic territory of the EU. The highest resolution available in our dataset is the NUTS 2 with in total 1166 regions (European Commission. Statistical Office of the European Union., 2022).

European agricultural sector (Aubert & Enjolras, 2018; Dabkiene et al., 2021; Grovermann et al., 2021; Slijper et al., 2022), thanks to the availability of detailed farm-level structural and economic information. Our sub-dataset covers a period of seven years (2013 – 2019). This time frame was selected due to the consistency of available data during this period. Additionally, 2019 represents the most recent year for which data was accessible at the time of the data request. By incorporating a seven-year span, we aimed to mitigate potential spikes or anomalies resulting from singular events, such as specific climatic conditions in a given year.

The FADN data represents an unbalanced panel, meaning that units of observations change over time. Between 2013 and 2019, only 36% of observations were consistent in each year, indicating a relatively large turnover in the units of observation (see Annex, Table A4). The data covers 16 different EU member states in Central and Southern Europe (see Annex, Table A3). The selection of these specific countries was aligned with the project research case studies within which this research is conducted[8]. We selected a subset of the data that is especially relevant for pesticide use and crop protection. More specifically, we focus on 7 different types of farming, as defined by the FADN typology (see Table 1 for a description of the farming types included in our analysis).

Table 1. Farming types definition.

Principal Farming type [a]	**Description (according to Commission Regulation (EC) No 1242/2008)**
Specialist Arable	General cropping i.e. cereals, dried pulses and protein crops for the production of grain, oilseeds, potatoes, sugar beet, industrial plants, arable land seed and seedlings, other arable land, fallow land and forage for sale > 2/3 of standard output.
Specialist Horticulture	Fresh vegetables, melons and strawberries — market gardening and under glass, flowers and ornamental plants — outdoor and under glass, mushrooms and nurseries > 2/3 of standard output.
Specialist Vineyards	Vineyards > 2/3 of standard output.
Specialist Fruit Farms	Fruit and berries and citrus fruit > 2/3 of standard output.
Specialist Olive Farms	Olives > 2/3 of standard output.
Permanent Crops Mixed	Holdings in class 3 "Specialist Permanent Crops", excluding those in classes 35, 36 and 37
All Crops Mixed	General cropping and horticulture and permanent crops > 2/3 but {general cropping ≤ 2/3 and horticulture ≤ 2/3 and permanent crops ≤ 2/3}

[8]Details about the project are found here: https://sprint-h2020.eu/

Source: Commission Regulation (EC) No 1242/2008 of 8 December 2008 establishing a Community typology for agricultural holdings. [a] In this classification system, farms are assigned to a type based on the share of standard output generated by a certain crop type. For instance, when 2/3 of the standard output stems from cereal production, the farm is considered a "Specialist cereals, oilseeds and protein crops" farm. We rely on this classification and not a more detailed one, to ensure adequate sample sizes for both treatment and control group.

We excluded from the analysis farms under conversion and farmers having only some fields or crops under organic standards as these farms have different yield and price dynamics compared to fully certified organic farms. To identify and discard multivariate outlying observations that could lead to biased results, we used the Bacon approach, which is particularly suitable to identify outliers in large multivariate datasets (Billor et al., 2000). We used all continuous outcome and control variables of our regression to identify outliers in the Bacon approach. We undertook the identification of outliers separately for each farming type, given that the types of crops or cropping systems grown on a farm, determine the distribution of certain economic variables. As a result, within each farming type, we discarded among one up to three percent of observations (see details in Annex, Table A5). Our final sample includes 10,531 organic farms and a total of 151,560 non-organic farms. As shown in Figure 3, the highest share of organic farms is found on agricultural holdings specialized in olive production, while the lowest share is on arable farms. An overview of the share of organic farms by farming type and country is provided in Annex, Table A4.

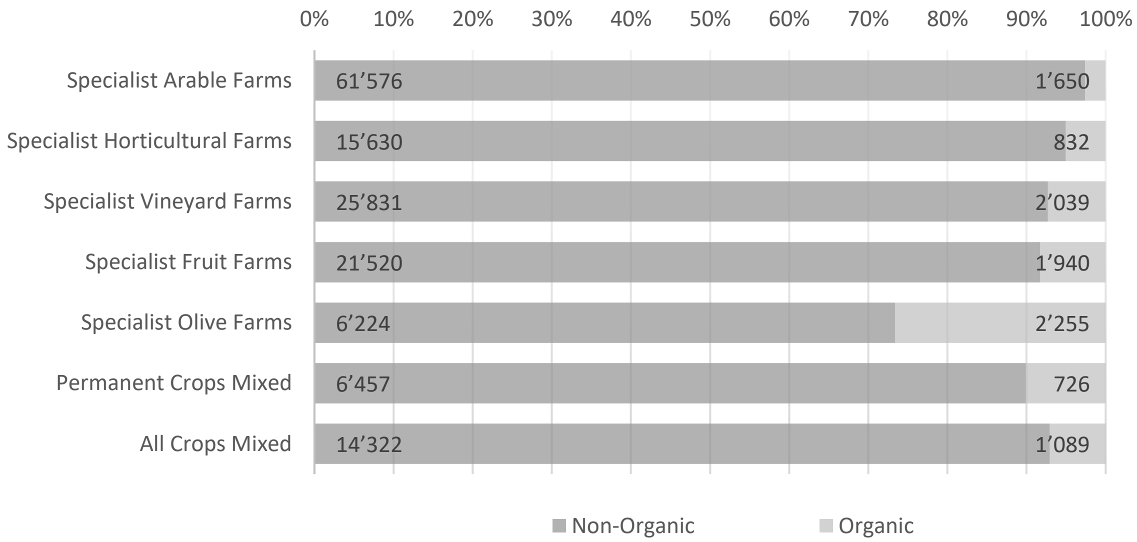
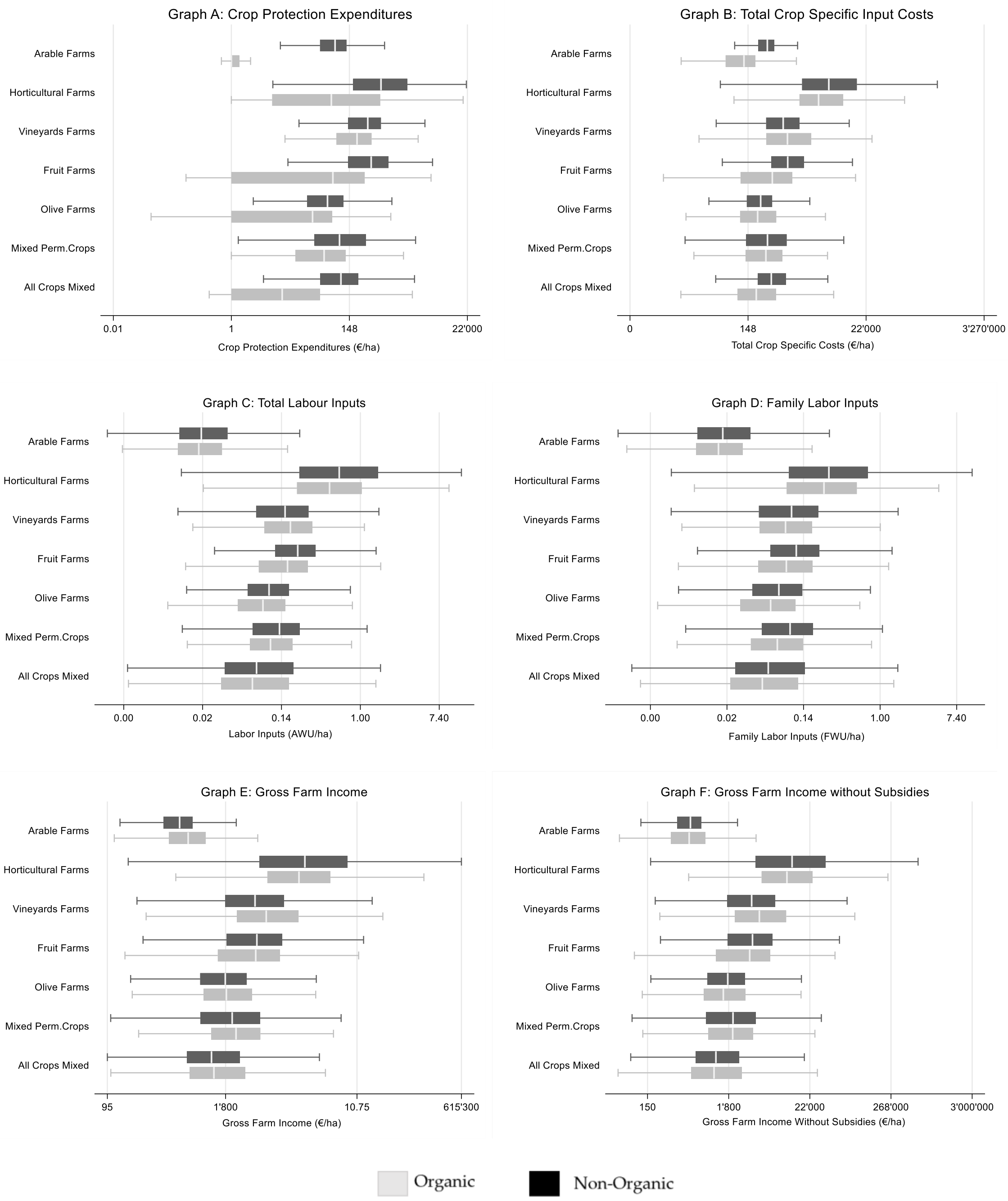


Figure 3*. Sample size of organic and non-organic farms for each farming type. After discarding outliers based on the Bacon approach, the dataset we used in our analysis includes a total sample N of 162'091 farms.*

Table A6 in the Annex provides an overview on some descriptive farm characteristics for both the treated (i.e. organic farms) and the control group (i.e. non-organic farms). When comparing the means across the two groups, significant differences for many of the covariates included in our analysis are found. The presence of such differences underlines the importance to implement measures that ensure the comparability among the two groups.

Figure 4 visually displays a simple comparison of distributions for each of the performance indicators.



Notes: The line splitting the box in two represents the median value. The left edge of the box corresponds to the first quartile, while the right edge corresponds to the third quartile. The lines extending from the boxes depict outliers in the dataset. The sample sizes for each farming type are reported in Figure 2.

Figure 4 illustrates the variations in crop protection expenditures per hectare (graph A), total crop specific costs per hectare (graph B) labour inputs per hectare (graph C), family labour inputs per hectare (graph D) and gross farm income with subsidies per hectare (graph E) and without subsidies per hectare (graph F) across different farming types and between organic and non-organic farms. Arable farms exhibit the lowest median crop protection expenditures per hectare, while vegetable farms have the highest. Additionally, median crop protection expenditures per hectare are consistently lower on organic farms across all farming types. The disparity between organic and non-organic farms is most pronounced in the case of arable farms, whereas the differences are less pronounced for other farming types. Notably, organic farms generally display greater variation in data. Total crop specific costs are lower on all farming types, except for specialist vineyard farms. Regarding labour inputs, arable farms overall have the lowest total labour inputs, while the labour input per hectare is highest for vegetable farms. Gross farm income per hectare is highest for vegetable farms and lowest for arable farms. Median gross farm income (including subsidies) tends to be higher on organic farms for all farming types, except in the case of vegetable farms (See Figure 4).

Although descriptive statistics provide an initial understanding of the data, they do not allow for a sound comparative assessment in terms of the economics of crop protection, while controlling for variation in other important characteristics. Therefore, we conduct a regression analyses to make a sound comparison of the economics of organic vs. non-organic farming. The results of these analyses will be presented in the following section.

4. ESTIMATION RESULTS

The results provide an overview on the effects of adopting and implementing organic farming on a set of economic performance indicators linked with the different crop protection strategies on both organic and non-organic farms. In section 4.1 we briefly outline the first stage estimation results. In section 4.2 we report the main estimation results of the inverse probability weighted regression adjustment estimator. These are displayed for each performance indicator for the seven farming types included in the analysis. For each outcome variable, we report the ATE in the form of a percent change, the respective robust clustered standard errors (SE), and the absolute changes (obtained by multiplying the percent change by the geometric mean of the weighted untreated group).

4.1. First stage estimation results

The first stage estimation results in an inverse probability weighted regression provide valuable insights into the relationship between the treatment assignment and the covariates. These results allow us to assess the extent to which the treatment assignment is influenced by the observed covariates used in the weighting procedure. In our study, various observed factors significantly impact the treatment assignment (i.e. the decision to adopt organic farming) across the different farming types (see Table B1 in the Annex). Notably, the share of income from other gainful activities, altitude and location consistently emerge as influential factors explaining the selection into treatment across all farming types. The influence of the other covariates i.e. farm size and size of the rented land on the selection into treatment, slightly differs between farming types. By conducting an inverse probability weighted regression analysis, we account for the observed covariates and their impact on the treatment assignment, resulting in more reliable estimates of the effects.

4.2. Effects on outcome variables

Our analysis unveils significant reductions in crop protection expenditures per hectare across all farming types following the adoption of organic farming practices (see Table 2). The ATE ranges from -40% to -96% across different farming types. Notably, specialist arable farms experience the most substantial reduction, with an ATE of -96%, resulting in an absolute decrease of approximately 62.48 €/ha. Moreover, organic farming consistently demonstrates cost-saving benefits in terms of total crop-specific costs per hectare. The ATE varies across farming types, ranging from -30% to -64%. Specialist arable farms exhibit a notable reduction, with an ATE of -64%, resulting in an absolute decrease of approximately 194.46 €/ha.

Our analysis indicates varied effects of organic farming on total labour inputs per hectare across different farming types. While some farming types witness marginal decreases in labour inputs, others experience slight increases. For instance, specialist horticulture, fruit, olives and mixed farms exhibit a significant reduction in labour inputs, with an ATE between -12 and 20%. Conversely, specialist vineyard farms observe a modest increase in labour inputs, with an ATE of 9%, corresponding to an absolute change of 0.01 annual working units per hectare. Organic farming demonstrates a consistent trend of reducing family labour inputs per hectare across all farming types. The ATE ranges from -7% to -19%, indicating notable decreases in family labour inputs following the adoption of organic practices. Specialist vineyard farms exhibit the most significant reduction, with an ATE of -19%, resulting in an absolute decrease of 0.01 family working units per hectare.

Without considering subsidies, our analysis reveals largely negative, but insignificant effects of organic farming on income (Table 2). However, when accounting for subsidies, we find largely positive impacts of organic farming on gross farm income per hectare, albeit with some variability across farming types. Arable farms and specialist vineyard farms experience a significant increase in gross farm income, with an ATE of respectively 22% and 21%, resulting in an absolute change of 118.12 €/ha and 796.75 €/ha. After accounting for subsidies, organic farming demonstrates mixed effects on gross farm income per hectare across different farming types. While some farming types experience marginal reductions in income, others witness slight increases.

Table 2. *Average Treatment Effect (ATE) of organic farming on outcome variables, by farming type.*

	Farming type						
	Specialist Arable	**Specialist Horticulture**	**Specialist Vineyard**	**Specialist Fruit**	**Specialist Olive**	**Mixed Permanent Crops**	**Mixed Crops All**
Total Sample	63,226	16,462	27,870	23,460	8,479	7,183	15,411
Crop Protection Expenditures per hectare							
ATE (% change)	-96%***	-87%***	-40%***	-84%***	-63%***	-68%***	-90%***
Standard Error	0.120	0.277	0.073	0.184	0.252	0.190	0.150
POM (€/ha)	64.78	479.14	253.15	270.70	40.49	92.85	87.97
Standard Error	0.069	0.153	0.144	0.100	0.172	0.157	0.100
ATE (change in €/ha)	-62.48	-417.21	-102.50	-227.10	-25.50	-63.36	-79.09
Total Crop Specific Costs per hectare							
ATE (% change)	-64%***	-30%**	11%	-55%***	-39%**	-39%**	-44%***
Standard Error	0.075	0.139	0.087	0.112	0.235	0.195	0.093
POM (€/ha)	304.30	4’684.43	639.70	715.51	219.42	320.22	403.43
Standard Error	0.035	0.148	0.137	0.082	0.131	0.139	0.076
Absolute change (€/ha)	-194.46	-1’393.26	68.69	-394.01	-85.40	-125.02	-178.68
Total Labour Inputs per hectare							
ATE (% change)	-2%	-20%**	9%	-18%***	-12%**	-15%**	-12%**
Standard Error	0.053	0.104	0.057	0.062	0.055	0.079	0.060
POM (AWU/ha)	0.02	0.56	0.14	0.18	0.12	0.12	0.08
Standard Error	0.063	0.123	0.097	0.061	0.081	0.081	0.096
Absolute change (AWU/ha)	-0.00	-0.11	0.01	-0.03	-0.01	-0.02	-0.01
Total Family Labour Inputs per hectare							
ATE (% change)	-7%	-16%*	-11%***	-13%***	-11%**	-18%***	-19%***
Standard Error	0.048	0.100	0.044	0.050	0.052	0.075	0.059
POM (AWU/ha)	0.02	0.25	0.09	0.10	0.06	0.09	0.06
Standard Error	0.074	0.112	0.108	0.067	0.193	0.091	0.108
Absolute change (AWU/ha)	-0.00	-0.04	-0.01	-0.01	-0.01	-0.02	-0.01
Gross Farm Income per hectare							
ATE (% change)	22%***	-11%	21%**	1%	-1%	3%	10%
Standard Error	0.057	0.122	0.075	0.075	0.089	0.097	0.065
POM (€/ha)	530.60	12’481.46	3’785.75	3’470.31	1’659.05	2’038.56	1’367.86
Standard Error	0.037	0.141	0.117	0.075	0.112	0.103	0.076

	Farming type						
	Specialist Arable	**Specialist Horticulture**	**Specialist Vineyard**	**Specialist Fruit**	**Specialist Olive**	**Mixed Permanent Crops**	**Mixed Crops All**
Total Sample	63,226	16,462	27,870	23,460	8,479	7,183	15,411
Absolute change (€/ha)	118.12	-1’400.32	796.75	46.82	-19.79	62.71	141.59
Gross Farm Income without Subsidies per hectare							
ATE (% change)	-1%	-11%	15%*	-5%	-14%	-11%	-5%
Standard Error	0.063	0.123	0.0807	0.075	0.0936	0.1	0.0719
POM (€/ha)	508.26	12’271.07	3’707.08	3’258.43	1’592.40	1’950.81	1’308.98
Standard Error	0.037	0.139	0.118	0.0728	0.113	0.107	0.0763
Absolute change (€/ha)	-5.56	-1’289.21	540.05	-158.92	-225.91	-215.40	-70.05

Notes. Significance levels: *** = p < 0.001, ** = p < 0.01, * = p < 0.05. SE = Standard Error. POM = Potential Outcome Mean.

4.3. Robustness checks

Sensitivity to omitted variable bias

Using the approach proposed by Diegert, Masten and Priorier (2022) we compute the breakdown point r_X^{bp} that characterizes the magnitude of selection on unobservable relative to selection on observables needed to overturn one’s baseline findings. Table 3 reports the breakdown points for three different outcome variables and each farming type given different levels of exogeneity, expressed by $\bar{c}$. Values of $\bar{c} > 0$ allow for partially endogenous controls. Based on the results, the effects of organic farming on crop protection expenditures per hectare seem relatively robust to omitted variable bias. The sensitivity analysis shows that selection on unobservable must be on average as large as up to 84% relative to selection on observables to overturn the baseline results, when allowing for partially endogenous controls ($\bar{c}$ = 1). When allowing for an increased degree of exogeneity ($\bar{c}$ closer to 0), the magnitude of selection on unobservable relative to selection on observables substantially increases, reaching on average a magnitude of 218%. For the outcome variables total labour inputs and gross farm income, the breakdown points (when $\bar{c}$ = 1) are on average relatively lower (respectively 27% and 31%), indicating a slightly higher risk that the results might be overturned in case of high omitted variables bias[9].

Table 3. *Overview of breakdown points by outcome variable, farming type and different levels of cbar.*

	Breakdown point (r_X^{bp}) % per Farming type							
	Specialist Arable	**Specialist Hortic.**	**Specialist Vineyard**	**Specialist Fruit**	**Specialist Olive**	**Mixed Perm.**	**Mixed All.**	*Average*
Crop Protection Expenditures per hectare								

[9] Note that r_X^{bp} must always be interpreted as dependent on the set of calibration controls.

$\bar{c}$ = 0	671	346	141	244	57	89	309	265
$\bar{c}$ = 0.25	254	189	107	155	51	75	178	144
$\bar{c}$ = 0.50	159	133	90	117	49	68	128	106
$\bar{c}$ = 0.75	118	106	82	98	49	67	104	89
$\bar{c}$ = 1	99	96	82	93	49	67	95	83
Total Labour Inputs (AWU/Hectare)								
$\bar{c}$ = 0	3	63	40	71	18	29	23	35
$\bar{c}$ = 0.25	3	56	37	62	18	27	23	32
$\bar{c}$ = 0.50	3	53	37	58	18	27	23	31
$\bar{c}$ = 0.75	3	53	37	58	18	27	23	31
$\bar{c}$ = 1	3	53	37	58	18	27	23	31
Gross Farm Income per hectare								
$\bar{c}$ = 0	80	29	63	9	1	11	27	31
$\bar{c}$ = 0.25	68	28	56	9	1	11	26	28
$\bar{c}$ = 0.50	63	28	54	9	1	11	26	27
$\bar{c}$ = 0.75	62	28	54	9	1	11	26	27
$\bar{c}$ = 1	62	28	54	9	1	11	26	27

Source: The breakdown point r_X^{bp} represents the magnitude of selection on unobservable relative to selection on observables needed to overturn one's baseline findings and is calculated using the "regsensitivity" command in STATA17. Note that r_X^{bp} must always be interpreted as dependent on the set of calibration controls.

5. Discussion

We find significant smaller plant protection products expenditures per hectare across all farming types for organic farms. Specifically, when considering arable farms, organic practices result in minimal spending on crop protection. We assume this can be attributed to the prevalent use of preventive strategies and the use of alternatives to plant protection products (e.g. mechanical weed control instead of herbicides). It is worth noting that the costs associated with these practices, such as fuel expenses, may not be fully captured by the analysed crop protection expenditure indicator. Additionally, it is important to acknowledge that implementing organic plant protection strategies incurs additional costs, such as transitioning to a new production system (i.e. knowledge acquisition, investment in new technology) or certification expenses. These costs are not reflected in the recorded crop protection expenditures indicator. As a result, the unaccounted costs may potentially reduce or alter the magnitude and significance of the observed effects. Nevertheless, our findings challenge the assumption that organic farms experience higher input costs due to elevated prices of biopesticides or increased frequency of sprayings (Bolda et al., 2019). Moreover, even though this analysis did not assess the environmental performance in relation to crop protection due to a lack of data, the lower costs observed in organic farming may indirectly suggest a reduction in pesticide usage and associated risks. However, caution should be exercised in drawing definitive conclusions, as pesticide costs do not consistently serve as reliable indicators of pesticide risk for the environment and human health (Möhring et al., 2019; Uthes et al., 2019). The findings not only unveil lower crop protection expenditures per hectare but also highlight reductions in total crop specific costs per hectare across various farming types. These results underscore the substantial cost-saving benefits of embracing organic farming, indicating that these benefits extend beyond mere crop protection expenditures to encompass overall input costs.

Despite inconclusive findings in the existing literature regarding differences in labour inputs between organic and non-organic farming, it is commonly believed that organic farming generally involves increased labour demand and costs (EC, 2023; Reissig et al., 2016; Sujianto et al., 2022). Our results, based on a comprehensive analysis of a large sample of farms across the EU, counter this widely held belief if focusing on farm-level labour inputs. We find that the disparity in total farm labour as documented in the FADN data between organic and non-organic farms is, in fact, minimal. But it depends on farm types. For example, slight increases or even decreases are observed both when looking at total labour inputs as well as when looking specifically at family labour inputs. Such heterogeneity is reflected in the findings of previous studies (e.g. (Orsini et al., 2018b). Because of the nature of the data, which provides us with an aggregated figure of labour (i.e. not disaggregated by farming activity) we are left with the following possible explanations (see e.g. (Avital, 2019; Padel & Lampkin, 1994; Spruijt-Verkerke, 2004) of the results regarding the amount of labour required to implement organic crop protection strategies: i) organic farms can adjust the farming system in way that for example pest pressure is avoided and thus the number of interventions can be reduced, ii) organic farms adjust their production portfolio and overall strategies to also comply with potential limits in labour supply, i.e. chose strategies to avoid increases in labour demand, iii) the labour inputs associated with organic crop protection strategies are not higher on organic farms, iv) the higher crop protection labour requirements are compensated by lower labour requirements on other activities and v) the higher labour requirements are satisfied through alternative forms of unpaid labour, such as apprentices or volunteers, not covered by the FADN data collection. Unfortunately, due to data limitations we are unable to make a more in-depth analysis focusing on differences related to labour activities specific to crop protection. Finally, our results do not back up the hypothesis that organic farming would increase the amount of on-farm job opportunities in rural areas of the EU, as suggested by a previous study in other regions (Finley et al., 2018). Nevertheless, the creation of employment might occur at other levels of the value chain.

On the revenue side, organic farming leads to higher gross farm incomes but only when accounting for subsidies. This positive effect is evident across all seven farming types examined, with a particularly notable impact on arable farms. However, after subtracting the subsidies from gross farm income, organic production appears to result in slightly less profitability for four of the farming types. Although these effects are not statistically significant, they highlight the significant role that subsidies play in ensuring a positive economic performance on organic farms. Therefore, in order to promote organic farming as an economically viable alternative under the Farm to Fork strategy, it is crucial to maintain appropriate levels of subsidies. Specifically, subsidies under the second pillar that promote production quality are recommended to encourage the adoption of greening measures, which are associated with reduced pesticide use (Aubert & Enjolras, 2018).

Both organic and non-organic farms derive varying degrees of benefit from their participation in Agri-Environmental Schemes (e.g. Schaub et al. 2023). It is essential to acknowledge that such participation can potentially influence the outcome variables we have analysed. However, the available data does not permit us to differentiate between the participation of farms in these schemes. Consequently, the effects we have attributed thus far to organic farming should be regarded as a combined effect, encompassing both the impacts of organic farming practices and participation in Agri-Environmental Schemes.

The different robustness checks we integrated in our analysis[10] allow for a more in-depth understanding of the results. On one side, the sensitivity analysis to omitted variables bias, shows that notwithstanding the lack of some possibly relevant confounding variables (e.g. individual farmer characteristics) in the here used database, our model results are for the most part robust across the different indicators and farming types. On the other side, the sample split according to farm size and geographic region, reveals heterogeneity in terms of magnitude, sign and significance of the effects across more narrowly defined farm structures and geographic regions.

Importantly, the results of our analysis are based on data covering the period between 2013 and 2019. Therefore, the validity of our results in the future will depend on how some of the factors that directly or indirectly influence the profitability of organic farming will change over time. In fact. the economics of organic farming might be disrupted, for instance, by the new regulations on plant protection products, which might see the ban of copper fungicides in organic farming across the EU (INRA, 2018). Moreover, the effects of an expansion of the volume of organic production might also affect the premium prices for EU organic products, which in turn might affect the economics of organic production. For farmers to realise sustained economic advantages from conversion, consumer demand in the future will need to keep up with policy goals.

[10] While our robustness checks provide valuable insights, it is important to acknowledge that some uncertainty remains, as these checks are not exhaustive.

Mainly due to the nature of the data, this study faces some limitations. If on one side FADN data represents a great resource to analyse the economics of European farming systems, given the relatively large sample sizes and the availability of data over time, on the other side it entails some shortcomings to specifically analyse the economics of organic agriculture and organic crop protection. For example, the unbalanced nature of the data set and the low number of switches to organic farming within the farms that are in the database for all years covered do not allow to employ standard approaches to identify the effect of switching to organic such as doubly robust difference in difference estimators (e.g.(Sant'Anna & Zhao, 2020) or regression discontinuity-based approaches (e.g. (Wuepper & Finger, 2023). Moreover, the FADN data lacks information on specific parameters that would allow a more accurate comparative analysis recognizing the heterogeneity in the integration of different crop protection approaches within both organic and non-organic farms. For instance, data on the implementation of specific weed, pest and disease management practices is not available. Also, the amount of labour is measured at the farm level (i.e. across all activities), which does not allow to draw more specific conclusions regarding the changes in labour inputs related to crop protection activities only. Moreover, the dataset does not include information on sales prices, which makes it unfeasible to disentangle the revenue effects and better understand the role played by premium prices. Moreover, the dataset used in this study does not cover all EU member states. Therefore, the geographic validity of our results cannot be extended to the entire EU territory. Despite the challenges driven by the nature of the data, this study provides valuable insights into the effects of adopting organic farming on crop protection expenditures and total crop specific costs per hectare, labour amounts per hectare, and farm income for European crop farmers, utilizing observational data from a harmonized EU level survey. Another important consideration in this analysis is that we do not assess the effects on productivity or environmental performance indicators associated with different crop protection strategies. These aspects are, of course, highly relevant in discussions regarding the Farm-to-Fork strategy (Barreiro-Hurle et al., 2022) .

6. Conclusion

We assess differences in terms of crop protection expenditures per hectare and total crop specific costs per hectare, total and family labour inputs per hectare, and overall gross farm income with and without subsidies per hectare between organic and non-organic farms, using a large cross-country dataset covering diverse farming systems in 16 EU countries. We show that organic farming significantly reduces crop protection expenditures per hectare and total crop specific costs per hectare. The magnitude of the estimated effects varies across farming types. The effects of organic farming on total labour inputs, family labour inputs and gross farm income (both with and without subsidies) are less marked and more heterogenous across farming types. The analysis clearly reveals the key role of subsidies in ensuring the economic viability of organic farms. Moreover, the sensitivity analysis on omitted variable bias provides confidence on the estimated effects. Finally, changes in the model specifications allowed us to identify potential variations in the effects across different farm sizes and geographic regions.

Our results provide valuable insights for farmers considering the transition to organic farming, revealing that adopting organic practices in various cropping systems can lead to cost savings in crop protection without a significant increase in labour requirements. This information is crucial for farmers to make informed decisions about the potential effects on labour resources when shifting to organic farming. Moreover, our results underline the fundamental role of subsidies in supporting the economic performance of organic farming. These subsidies are critical consideration for effective policy implementation to enlarge organic farming further. Finally, our heterogeneity analysis highlights the potential differences in effects across farm sizes and geographic regions. This underscores the importance of considering the specific contexts and characteristics of different farm sizes and regions when formulating policies and interventions related to organic farming.

Finally, based on our analysis, we have identified important areas for future research. Future studies may conduct a detailed comparative analysis across different, well-defined production systems that rely on lower pesticide use (e.g., IPM, Agroecological Crop Protection, or pesticide-free agriculture) to reveal economic performance and reveal underlying mechanisms. Moreover, there is a need to further explore the effects of organic farming on labour inputs for specific activities, also overcoming limitations associated with the here used FADN data. Additionally, researchers could broaden the scope by considering labour productivity indicators when evaluating the effects of organic farming practices. Moreover, conducting an analysis at the crop level would provide farmers with more practical information on the associated costs, yield effects and revenue changes in specific production systems. Lastly, integrating productivity or environmental risk indicators, such as the Pesticide Load Index, would enable an interesting analysis of economic and environmental trade-offs or synergies at the farm level.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve the readability of the text in some section. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Annex

A. Data

Table A1. Description of outcome variables

Indicator	Unit	Description
Crop protection expenditures	€/ha	$= SE300 / SE025$ SE300: FADN standard results variable for the farm-level expenditure for crop protection (including plant protection products, traps and baits, bird scarers, anti-hail shells, frost protection, etc.). SE025: the total utilized agricultural area (UAA) of a farm, in hectare (ha).
Total Crop specific Costs	€/ha	=SE284: Total crop specific costs per hectare, covering purchased fertilisers and soil improvers, plant protection products, soil analysis, purchase of standing crops, renting crop land for a period of less than one year, purchase of crop products (grapes, etc.), costs incurred in the market preparation, storage, marketing of crops.
Total Labour Input	Annual working units/ha	$= SE010 / SE025$ SE010: Total labour input of holding expressed in annual work units = full-time person equivalents. SE025: the total utilized agricultural area (UAA) of a farm, in hectare (ha).
Total Family Labour Input	Family working units/ha	$= SE015 / SE025$ SE015: Total unpaid labour input of holding expressed in annual family working units = full-time person equivalents. SE025: the total utilized agricultural area (UAA) of a farm, in hectare (ha).
Gross farm Income	€/ha	$= SE410 / SE025$ SE410: Total output from crops and livestock – total specific costs + subsidies - Intermediate consumption + Balance current subsidies & Taxes. SE025: the total utilized agricultural area (UAA) of a farm, in hectare (ha).

Gross farm income (without subsidies)	€/ha	$= (SE410 - SE610 - SE621) / SE025$ SE610: All farm subsidies on crops, including compensatory payments/area payments, set-aside premiums and aid under Art 68. SE621: Subsidies on environment and environmental restrictions.

Source: definition of variables as described in FADN handbook (European Commission, 2014). The variables nuts2 is used to cluster the standard errors.

Table A2. Description of covariate variables

Covariate	Unit	Description
Structural Farm Characteristics		
Farm size	ha	Total utilized agricultural area of holding. It includes agricultural land temporarily not under cultivation.
Rented area	ha	Utilized agricultural areas rented by the holder under a tenancy agreement for a period of at least one year
Other gainful activities	Categorical	Three categories are based on the output generated by other gainful activities: 1 = % ≤ 10 2 = 10 < % > 50 3 = 50 < % > 100
Irrigation	Dummy	Indicates whether the farm has or not irrigation. The variable takes a value of 1 when the farm has irrigation, and 0 otherwise.
Crop Insurance	Dummy	Indicates whether the farm has or not an insurance against crop losses. The variable takes a value of 1 when the farm has an insurance, and 0 otherwise.
Geo-spatial and temporal covariates		
Nuts2	Categorical	Basic regions for the application of regional policies
Altitude	Categorical	Codes indicating the location of the majority of the UAA of the holding: 1 = below 300 meters; 2 = from 300 to 600 meters; 3 = above 600 meters; 4 = data not available.

Year	Categorical	Indicates the year to which the observations belongs to.

Table A3. Distribution of farms by production system and country.

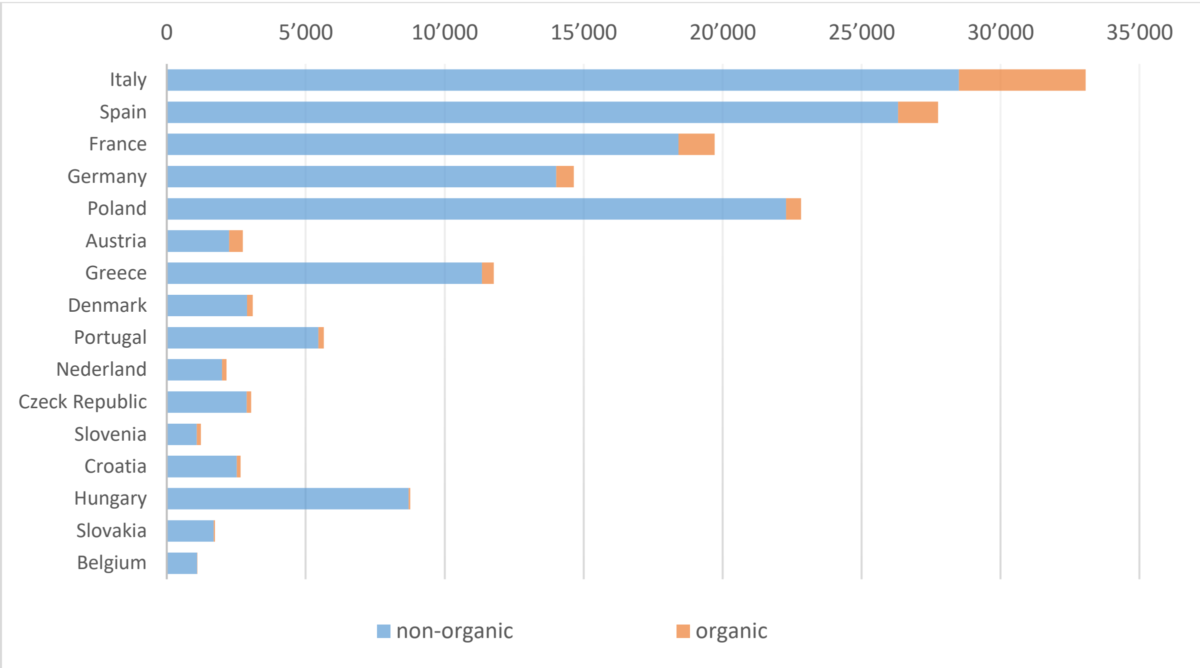

Table A4. Outlier Removal using the Bacon approach: changes in sample sizes by farming type.

TF14	Non-organic Farms: Before outlier removal (# farms)	Non-organic Farms: After outlier removal (# farms))	# dropped obs.	Organic Farms: Before outlier removal (# farms)	Organic Farms: After outlier removal (# farms)	# dropped obs.	Total # dropped obs.
S. Arable Farms	62’519	61’576	943	1’667	1’650	17	960
S. Vegetable Farms	15’994	15’630	364	863	832	31	395
S. Vineyards	26’213	25’831	382	2’059	2’039	20	402
S. Fruit Farms	21’916	21’520	396	1’958	1’940	18	414
S. Olive Farms	6’398	6’224	174	2’280	2’255	25	199
Perm. Crops Mixed.	6’603	6’457	146	745	726	19	165
All Crops Mixed	14’763	14’322	441	1’102	1’089	13	454

Total	**154’406**	**151’560**	**2’846**	**10’674**	**10’531**	**143**	**2’989**

Figure A1. Distribution of farms by country and farming type (tf14 classification).

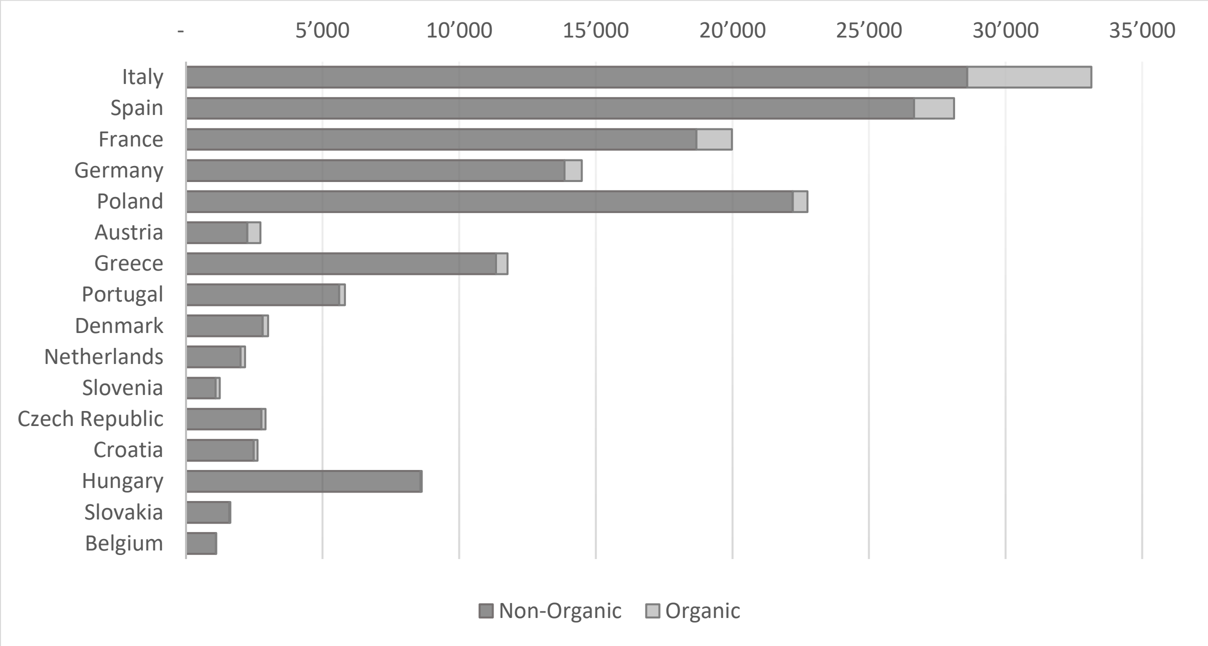

Table A6. Descriptive statistics for covariates.

	Mean non-organic	Mean Organic	Difference[a]	T/Z score[b]	Significance[b]
Specialist Arable					
Farm Size (ha)	124.93	113.85	-11.08	2.51	*
Rented land (ha)	79.99	66.65	-13.33	3.55	***
Irrigation (bin)	0.02	0.01	-0.01	2.85	**
Crop insurance (bin)	0.58	0.50	-0.07	5.78	***
OGA share	1.10	1.18	0.08	-9.64	***
Specialist Horticultural					
Farm Size (ha)	13.34	13.77	0.43	-0.56	NS
Rented land (ha)	6.65	6.40	-0.25	0.43	NS
Irrigation (bin)	0.08	0.06	-0.03	2.79	**
Crop insurance (bin)	0.38	0.29	-0.08	4.86	***
OGA share	1.07	1.14	0.07	-7.10	***
Specialist Vineyard Farms					
Farm Size (ha)	21.62	21.06	-0.56	0.96	NS
Rented land (ha)	10.06	11.02	0.97	-2.04	*

Irrigation (bin)	0.03	0.02	-0.01	3.19	**
Crop insurance (bin)	0.51	0.53	0.01	-1.26	NS
OGA share	1.09	1.11	0.02	-2.92	**
Specialist Fruit Farms					
Farm Size (ha)	16.22	18.91	2.70	-5.79	***
Rented land (ha)	6.13	6.89	0.76	-2.18	*
Irrigation (bin)	0.09	0.07	-0.02	2.31	*
Crop insurance (bin)	0.46	0.36	-0.10	8.12	***
OGA share	1.06	1.09	0.03	-4.92	***
Specialist Olive Farms					
Farm Size (ha)	16.96	21.27	4.30	-8.53	***
Rented land (ha)	4.35	5.14	0.78	-3.20	**
Irrigation (bin)	0.06	0.03	-0.04	6.49	***
Crop insurance (bin)	0.50	0.48	-0.02	1.56	NS
OGA share	1.05	1.07	0.02	-2.26	*
Permanent Crops Combined					
Farm Size (ha)	18.99	22.00	3.01	-3.37	***
Rented land (ha)	4.89	6.51	1.62	-3.59	***
Irrigation (bin)	0.08	0.08	-0.00	0.10	NS
Crop insurance (bin)	0.50	0.51	0.00	-0.24	NS
OGA share	1.09	1.15	0.06	-4.76	***
All Crops Mixed					
Farm Size (ha)	41.07	44.15	3.07	-1.79	NS
Rented land (ha)	19.38	20.85	1.47	-1.19	NS
Irrigation (bin)	0.08	0.05	-0.02	2.69	**
Crop insurance (bin)	0.50	0.44	-0.06	3.95	***
OGA share	1.10	1.25	0.16	-13.67	***

[a] The differences in means are obtained by subtracting means for certified farms from those for conventional farms. T-test is used to compare the differences for continuous variables. The test on the equality of proportions is used to compare the differences for binary variables and Z-score is reported. [b] ***, **, and * indicates statistical significance at 1%, 5%, and 10%, respectively. NS indicates "Not Significant".

B. Econometric analysis and Robustness Checks

Table B1. First stage estimation results

Variable	Speciali st Arable	Specialist Hortic.	Specialist Vineyard	Specialist Fruit	Specialist Olive	Mixed Perm.	Mixed All.
Sample size (N)	63'226	16'462	27'870	23'460	8'479	7'183	15'411
Farm Size	1.000 (0.000)	1.006* (0.003)	0.989*** (0.002)	1.011*** (0.001)	1.008*** (0.001)	1.001 (0.002)	1.000 (0.001)
Size of Rented area	0.999** (0.000)	0.992* (0.004)	1.005** (0.002)	0.996* (0.002)	0.999 (0.003)	1.004 (0.003)	1.000 (0.001)
Altitude	0.656*** (0.078)	1.118 (0.123)	0.249*** (0.021)	1.837*** (0.161)	0.711** (0.075)	0.417*** (0.066)	0.606*** (0.075)
Location	1.469*** (0.049)	0.654*** (0.052)	0.912* (0.038)	1.162*** (0.043)	0.802*** (0.029)	0.805*** (0.052)	1.160** (0.0539
Share of income other gainful activities	1.756*** (0.100)	1.866*** (0.176)	1.156* (0.077)	1.422*** (0.103)	1.184* (0.096)	1.494*** (0.139)	2.187*** (0.133)

Notes: All coefficients are exponentiated. Notes. Significance levels: *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$. Standard errors are reported into brackets.