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Conventional versus organic olive farming: which has a better economic performance?

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Abstract

The European Green Deal sets a target of at least 25% of the total EU agricultural land under organic farming by 2030. In the case of the Spanish olive sector, organic olive farming accounts for barely 10% of the national agricultural area dedicated to this crop. Within this context, this study compares the economic performance of Spanish conventional and organic olive farms in terms of productivity, profitability, viability, resilience, and independence. To do so, microdata provided by the Spanish Farm Accountancy Data Network have been used, and matching methods have been applied to conduct an unbiased comparative analysis of matched conventional and organic farms. Results show statistically significant differences in productivity, with conventional olive groves being more productive. However, CAP subsidies are shown to be an effective instrument for promoting the conversion to organic farming in olive groves since they cancel out the differences in profitability between these two production systems. There is also evidence of the greater resilience of organic farms. These results could contribute to a more efficient design of instruments promoting the ecological transition of agriculture in line with the aforementioned policy objective.

Keywords: Organic farming, Olive farms, Productivity, Profitability, Resilience

Introduction

Like many other economic sectors, agriculture generates significant environmental impacts. Agricultural production is a primary activity and therefore involves a highly intensive use of natural resources (soil, water, and energy) (Debertin 2012). This fact, together with the growing productive intensification of the agricultural sector (i.e., higher use of inputs to increase production), explains the significant negative pressures exerted on the planet's biodiversity, soil, and water resources (e.g., Parris 2011; Wezel et al. 2011; Montanarella and Panagos 2021). The Food and Agriculture Organization of the United Nations (FAO) shows that, among other agricultural practices, the increased use of agrochemicals, excessive mechanization of land use, monocultures, and grazing intensity are responsible for the main negative environmental externalities from the agricultural sector worldwide (FAO 2022).

The European Union (EU) is striving to lead the way in the reduction of the environmental impacts of agriculture and the development of more sustainable and resilient food systems. For this purpose, the Farm to Fork Strategy (European Commission

2020b) and the Biodiversity Strategy (European Commission 2020a) have been approved as part of the European Green Deal (European Commission 2019). Both strategies call for a reduction in the use of agrochemicals and the promotion of agroecological practices, establishing a series of specific objectives for 2030: a) to reduce the overall use and risk of chemical pesticides and the use of more hazardous pesticides by 50%; b) to reduce the use of fertilizers by at least 20%, thereby reducing nutrient losses by at least 50%; c) to reduce overall EU sales of antimicrobials for livestock farming and aquaculture by 50%; and d) to have 25% of agricultural land in the EU under organic farming. Accomplishing these objectives will require the active involvement of farmers, who must find innovative solutions to meet these new social and political demands and reduce environmental impacts while maintaining the productivity and competitiveness of the European agricultural sector (Malorgio and Marangon 2021).

Regarding the last specific objective of the European Green Deal, according to the latest Eurostat data, only 9.1% of the EU's utilized agricultural area (UAA) was under organic farming in 2020. Thus, there is a clear need to promote this agroecological production system during the coming years in order to meet the target of 25% by 2030. Compared with conventional farming, organic farming makes more extensive use of resources; in particular, it makes significantly less use of pesticides and fertilizers, resulting in lower yields (de Ponti et al. 2012; Seufert et al. 2012). As a direct consequence, the profitability of organic farms is usually lower, which is the main factor explaining low conversion rates across the EU Member States (European Commission 2023). However, the profitability gap between conventional and organic farming has been shrinking in recent years for two main reasons.: On the one hand, the growing demand for certified organic food and the consequent price premium over conventional agricultural products (Tandon et al. 2021). On the other hand, the public financial support provided to organic farming, which in the case of the EU is implemented through subsidies allocated under the second pillar of the Common Agricultural Policy (CAP). Both of these reasons help explain the recent growth in the area dedicated to organic agriculture in the EU, as the last report of the International Federation of Organic Agriculture Movements (IFOAM) points out (Willer et al. 2023). In any case, it is reasonable to assume that the expansion of this type of agriculture in the future will depend on the evolution of its relative profitability compared to conventional agriculture.

Considering the target of 25% of the agricultural area under organic agriculture set by the European Green Deal, it is only by bridging the profitability gap between the two production systems that the conversion from conventional to organic farming can be effectively promoted. Within this context, the main objective of this work is to compare the economic performance of organic and conventional farms, taking the Spanish olive sector as the case study. For this purpose, a comprehensive assessment approach is proposed, allowing us to test for significant differences between conventional and organic olive farms regarding each economic performance dimension considered: productivity, profitability, viability, resilience, and independence. By so doing, we can highlight the factors on which political action should be focused to ensure that the organic transition process occurs at the rate required by the European Green Deal, while minimizing the negative effects arising from the loss of production.

Previous comparative analyses of conventional and organic farms' economic performance have usually employed a non-randomized approach, directly comparing samples of conventional and organic farms (e.g., Demiryurek and Ceyhan 2008; Acs et al. 2009; Artukoglu et al. 2010; Beltrán-Esteve and Reig-Martínez 2014). Hence, these studies fail to consider variables that affect the farmers' adoption of the organic production system (sample self-selection bias) and the farms' economic performance (structural and productive differences). Consequently, the differences in farms' performance obtained in these analyses could be significantly biased, as it may be the case that instead of being caused by the production system implemented (i.e., conventional vs. organic), they are actually explained by underlying factors such as farmers' demographic variables (e.g., age and education) and farms' structural characteristics (e.g., size and location) that lead to dissimilarities between the samples compared (Froehlich et al. 2018; Raimondo et al. 2021).

To address this limitation, several authors have employed matching methods when conducting farm-level comparative assessments (e.g., Mayen et al. 2010; Uematsu and Mishra 2012; Gillespie and Nehring 2013; Froehlich et al. 2018). These statistical techniques (further explained in the methodology section) attempt to balance the distribution of a set of control variables (i.e., covariates such as farmers' age or farm size) between the samples compared, preventing potential biases due to differences in these variables between the samples (Stuart 2010; Ho et al. 2011). Thus, following the most recent literature, we applied a matching technique to compare two samples of olive farms (conventional and organic), employing a quasi-experimental approach that allowed us to estimate the unbiased impact of organic production (compared to conventional farming) on farms' economic performance. To the best of the authors' knowledge, only Raimondo et al. (2021) have previously employed matching methods to compare the economic performance of organic and conventional olive farms. They used this approach to examine differences in technical efficiency in Italian olive farms, comparing a sample of 103 organic and 252 conventional olive farms, considering data from a single year (2015). The analysis showed that organic farming could increase technical efficiency in Italian olive farms by approximately 10%.

This paper aims to contribute to the existing literature in several ways. First, the analysis relies on a comprehensive conceptualization of farms' economic performance, drawing on an extensive literature review. This has allowed a thorough and innovative assessment of farms' economic performance based on five key dimensions: productivity, profitability, viability, resilience, and independence. Second, we used matching methods for an unbiased comparative analysis of farms' performance in three different years (2014, 2018, and 2020), thus accounting for the dynamic nature of the agricultural sector (i.e., volatility in economic performance) while testing the robustness of the results obtained for "average", "good", and "bad" agricultural seasons from an economic point of view. And third, this is the first study to apply these methodological techniques to analyze the performance of farms specialized in permanent crops; specifically, olive (the study by Raimondo et al. 2021 focused solely on technical efficiency). All these contributions help expand the state of the art in the field of research on farm-level economic performance measurement and comparative assessment.

The rest of the paper is organized as follows. Section 2 outlines the general situation of the olive sector in Spain and the main descriptive statistics of the representative sample of olive farms considered for the empirical analysis. Section 3 presents the indicators selected to assess the economic performance of the farms and the matching method employed to replicate a randomized experiment for the comparison of organic and conventional olive farms. The main results and discussion are addressed in Sect. 4. Finally, Sect. 5 contains the main conclusions drawn from the comparison of organic and conventional olive farms to support a more efficient design of the policy instruments promoting organic farming.

Case study and data source

Organic olive farming in Spain

In order to justify the relevance of the comparative analysis proposed, we must highlight the importance of organic olive farming in Spain. In this respect, according to the latest Spanish agricultural census (INE, 2022), in 2020, there were 18,147 olive farms in Spain certified as organic (7.3% of the total Spanish olive farm population), covering an area of 220,902 hectares (10.4% of the national UAA devoted to olive groves). As shown by the data published by the Spanish Ministry of Agriculture, Fisheries, and Food (MAPA 2022), there has been a continuing rise in the number of organic farms and the organic farming area over the last two decades, and they have reached a historic high. Two factors can explain this trend. First, the organic production of extra virgin olive oil has become an increasingly attractive niche market for olive oil producers, responding to consumers' willingness to pay higher prices for this type of oil (Cabrera et al. 2015; Del Giudice et al. 2015). Second, the increase in subsidies for organic farming from the second pillar of the CAP has improved organic farms' revenues. Both factors have partially offset the profitability gap faced by organic olive growers.

Data source

Any comparative analysis of the economic performance of conventional and organic farms must necessarily be based on microeconomic data at the farm level since only those data adequately reflect the heterogeneity of farms in terms of their ability to generate income and remunerate the factors of production used in both production systems. In this sense, the information provided by the Farm Accountancy Data Network (FADN) is the best option available in the EU. In our case, the analysis was based on the microdata of the representative sample of farms provided by the Spanish branch of the FADN (*Red Contable Agraria Nacional*, RECAN), using only those data obtained from farms coded as Type of Farming 37 (TF 37, olive farming) during the 2014–2020 period.

As Table 1 shows, the olive farm sample size in the RECAN has increased from 350 to 435 over the period considered. On average, organic farms represent a third of the sample and about 30% of the sampled area. According to these figures, organic farms are overrepresented in the FADN sample. However, this is not a problem for our study since this overrepresentation ensures we have a minimum number of farms of each type to carry out the comparative analysis proposed.

Table 1 RECAN TF 37 annual sample distribution of conventional and organic farms

Category	Units	2014	2015	2016	2017	2018	2019	2020	Mean
Conventional farms	Farms	231	246	222	227	244	286	290	249
	%/sample	66%	66%	67%	66%	67%	67%	67%	67%
	UAA	8,035	10,460	10,966	11,231	11,912	12,680	13,382	11,238
	%/sample	65%	65%	69%	67%	74%	70%	70%	68%
Organic farms	Farms	119	127	108	119	120	141	145	126
	%/sample	34%	34%	33%	34%	33%	33%	33%	33%
	UAA	4,319	5,716	4,942	5,564	4,144	5,533	5,699	5,131
	%/sample	35%	35%	31%	33%	26%	30%	30%	32%
Total	Farms	350	373	330	346	364	427	435	375
	%/sample	100%	100%	100%	100%	100%	100%	100%	100%
	UAA	12,354	16,176	15,908	16,795	16,056	18,213	19,081	16,369
	%/sample	100%	100%	100%	100%	100%	100%	100%	100%

Source: Own elaboration based on RECAN microdata

Economic performance of the Spanish olive sector

Before comparing conventional and organic olive farms, we conduct a brief analysis of the situation of the Spanish olive sector at the microeconomic level to help ensure the proper interpretation of the results derived from the study.

Table 2 shows some economic performance indicators of the average Spanish olive farm during the 2014–2020 period. As the data suggest, the annual volatility of the revenues, mainly due to variations in yields and world olive oil prices, leads to significant variations in the annual profitability indicators. This production and profitability volatility justifies the long period (2014–2020) used to analyze the economic performance of these farms, as it allows an assessment of the changing factors affecting their performance.

As can be seen in Table 2, while Spanish olive farms' subsidies and cost variables remain relatively stable during the period (with a CV of 5.2% and 5.8%, respectively), their sales revenue is highly volatile (CV = 9.3%) depending on crop yields, primarily due to weather variability. This in turn leads to highly volatile olive farm income (i.e., indicators GFI, FNVA, and FNI, with a CV of 8.9%, 9.8%, and 12.5%, respectively). Thus, considering the available data provided by the RECAN and their evolution over time, we focused on three specific years from the analyzed period: 2014, 2018, and 2020, representing "bad", "good", and "average" seasons, respectively, in terms of economic performance (i.e., revenue and income). Therefore, by choosing these seasons for the empirical study, we dealt with the dynamic nature of the olive sector mentioned above; that is, we took into account the conditions that olive growers face and their capacity for adaptation (i.e., resilience) under alternative economic scenarios in this sector.

The RECAN does not publish aggregate data on the olive sector broken down into types of production system (e.g., conventional vs. organic). However, using microeconomic data at the farm level (i.e., considering all olive farms sampled by the RECAN) allowed us to assess the differences in economic performance between conventional and organic farms for each season.

Table 2 RECAN summary information on TF 37 (olive farming)

Variable	FADN code	2014	2015	2016	2017	2018	2019	2020	Mean	CV (%)[a]
Farms represented	SYS02	49,921	50,273	55,385	55,388	55,488	55,657	55,863	53,996	4.6
Sampled farms	SYS03	350	373	330	346	364	427	435	375	10.0
Structure										
Total UAA (ha)	SE025	25.3	27.2	25.4	27.9	25.8	25.7	25.9	26.2	3.5
Total labor input (AWU[b])	SE010	1.40	1.50	1.30	1.30	1.40	1.30	1.30	1.36	5.4
Unpaid labor input (AWU)	SE015	0.80	0.80	0.70	0.70	0.70	0.70	0.70	0.73	6.2
Paid labor input (AWU)	SE020	0.60	0.60	0.60	0.50	0.70	0.60	0.60	0.60	8.9
Revenues (€/ha)										
Sales revenue	SE131	1492	1936	1860	1811	2103	1913	1895	1859	9.3
Subsidies	SE605	483	464	420	422	471	436	436	447	5.2
Costs (€/ha)										
Total inputs	SE270	1207	1250	1184	1077	1297	1281	1280	1225	5.8
Intermediate consumption	SE275	654	656	598	612	721	715	713	667	7.0
Depreciation	SE360	183	204	198	165	172	173	162	180	8.3
External factors	SE365	371	390	389	301	405	393	405	379	8.9
Wages paid	SE370	321	350	346	263	361	348	362	336	9.6
Rent paid	SE375	44	36	38	36	41	42	40	40	7.1
Interest paid	SE380	5	4	5	2	3	3	3	4	29.4
Income (€/ha)										
Gross Farm Income (GFI)	SE410	1369	1814	1676	1616	1856	1638	1623	1656	8.9
Farm Net Value Added (FNVA)	SE415	1185	1610	1478	1451	1684	1465	1461	1476	9.8
Farm Net Income (FNI)	SE420	802	1161	1087	1149	1283	1071	1062	1088	12.5

[a] Coefficient of variation

[b] Annual Work Unit

Source: Aggregate economic results published annually by the RECAN

Methodology

The methodology employed for the analysis can be split into four steps. First, we conducted an extensive literature review to conceptualize farms' economic performance and choose the appropriate indicators for its assessment. Second, we calculated the economic performance indicators for every farm included in the two samples considered (i.e., conventional and organic). Third, we implemented a matching procedure to these samples to eliminate biases associated with the influence of underlying factors (non-randomization). This step involved the selection of both the matching method to be implemented and the set of covariates included in the analysis to achieve a balance between samples. Lastly, using the average treatment effect (ATE) estimator, we calculated the treatment effect (i.e., conversion to organic olive growing) on every economic performance indicator chosen, identifying which ones are statistically significantly affected (positively or negatively) by the olive farms' conversion to organic farming.

Economic performance indicators

The assessment of farms' economic performance is a recurring topic in the literature since good economic performance (i.e., economic sustainability) is a *sine qua non* for the continuity of farms' productive activity. Therefore, this is a topic of interest in both the political and academic arenas. Despite this, there is no commonly accepted conceptualization of farms' economic performance. While there is a consensus about its multidimensionality, there is no unanimous agreement on a classification or typology of its dimensions. As a result, multiple approaches for the quantitative analysis of this concept have emerged, varying in the dimensions considered and the indicators used to measure them, as pointed out by Spicka et al. (2019) or Coppola et al. (2022).

In this study, we used a comprehensive approach for the assessment of farms' economic performance, including the dimensions of economic performance that the academic literature has deemed most relevant: productivity, profitability, viability, resilience, and independence. Thus, a set of 32 economic performance indicators have been calculated for each farm and year using the microdata provided by the RECAN. Table 3 shows the average values of these indicators for conventional ($n=246$) and organic ($n=130$) olive Spanish farms in 2020.[1] Furthermore, Table 6 in Appendix 1 details how these indicators were calculated at the farm level. Below, we explain the selected economic performance indicators.

Productivity can be defined as the relationship between a firm's production and the resources used to obtain it. Despite the availability of more sophisticated methodological options (e.g., Islam et al. 2014; Rada and Fuglie 2019), the quantitative analysis of productivity in this study has been based on a classical perspective, considering the partial productivity of the three basic production factors: land, labor, and capital, as proposed by van Passel et al. (2007) and Onofri et al. (2019), among others. Therefore, the three productivity indicators have been calculated by dividing the value of the farms'

[1] Although for 2020 the RECAN collected data for 290 conventional and 145 organic olive farms, some of the farms lack information on covariates such as age or education. The farms with incomplete information were dropped from the sample for the empirical analysis, leaving 246 conventional and 130 organic olive farms with full information.

Table 3 Average values of economic indicators for the organic and conventional olive farms for the year 2020 ("average" season)

Indicator	Organic farms ($n = 130$)	Conventional farms ($n = 246$)	Organic-conventional difference	
			Difference	t statistic
Productivity				
Land productivity (€/ha)	1391	2139	− 747	6.64***
Labor productivity (€/AWU)	34,030	41,959	− 7929	2.51*
Capital productivity (%)	14.3	17.5	− 3.14	2.49*
Profitability				
1. Sales revenue (€/ha)	1391	2139	− 747	6.64***
2. CAP subsidies (€/ha)	507	400	107	− 2.77**
CAP 1st pillar subsidies (€/ha)	272	377	− 105	3.35***
CAP 2nd pillar subsidies (€/ha)	235	24	212	− 12.1***
A. Total revenue (€/ha)	1899	2539	− 640	5.24***
3. Intermediate consump. (€/ha)	519	781	− 262	5.75***
B. Gross margin (€/ha)	1380	1758	− 378	3.93***
4. Wages paid (€/ha)	263	340	− 76.6	2.50*
5. Rent paid (€/ha)	17.1	25.9	− 8.8	1.26
6. Depreciation (€/ha)	213	195	18.4	− 0.89
C. EBIT (€/ha)	886	1198	− 311	3.51***
D. EBT (€/ha)	886	1196	− 310	3.50***
E. Net income (€/ha)	866	1173	− 307	3.46***
ROA (%)	9.62	9.69	− 0.08	0.08
ROE (%)	9.44	9.51	− 0.08	0.08
Viability				
Total opport. costs (TOC) (€/ha)	738	882	− 144	2.99**
Economic profit (€/ha)	128	290	− 162	1.69
Long− term econ. viability[a]	1.39	1.69	− 0.29	1.81
Short− term econ. viability[a]	11.31	8.44	2.90	− 0.80
Resilience				
CV of net income (%)	42.4	56.5	− 14.1	2.35*
Net income resistance (%)	− 47.4	− 106	58.1	− 1.17
Shannon div. index (SDI)[a]	0.028	0.097	− 0.069	2.87**
Specific costs adjus. flexibility (%)	141	41.2	99.8	− 8.12***
Labor input adjus. flexibility (%)	32.8	32.2	0.63	− 0.20
SDI adjus. flexibility (%)	0.95	0.73	0.21	− 0.47
Independence				
Revenue dependency (%)	29.0	16.6	12.4	− 6.90***
Net income dependency (%)	8.97	− 23.9	32.8	− 0.48

***, **, and * denote statistical significance at 0.1%, 1%, 5%, respectively

[a] Dimensionless variable

Source: Own elaboration based on RECAN microdata

production in euros by the quantities of the three factors employed: land measured in hectares, labor in Annual Work Units (AWU), and capital (i.e., total assets) in euros (see Table 6 in Appendix 1).

Profitability can be characterized as the relationship between the profits generated by a firm and the investments or resources allocated to run the business. This is one of the most extensively studied dimensions of economic performance since it enables the assessment of whether farms generate higher or lower profits than alternative businesses (Coppola et al. 2020). The assessment of this dimension was based on a traditional approach (e.g., Uematsu and Mishra 2012; Gillespie and Nehring 2013), accounting for both income statement indicators and pure profitability indicators, as shown in Table 3. The former include revenue (sales and subsidies), variable costs and overhead costs, and the corresponding gross margin, earnings before interest and taxes (EBIT), earning before taxes (EBT), and net income; while the latter are return on assets (ROA) and return on equity (ROE). These sets of indicators not only allow us to detect differences in farms' profitability (i.e., ROA and ROE) but also facilitate the interpretation of these potential differences (i.e., income statement indicators), enabling us to identify some possible causal effects.

The definition of farm *viability* has generated multiple academic debates, as evidenced by O'Donoghue et al. (2016) or Loughrey et al. (2022). However, many authors (e.g., Argilés 2001; Vrolijk et al. 2010; Spicka et al. 2019; Coppola et al. 2022) conceptualize this term as the farms' capacity to generate sufficient income to cover all fixed and variable costs, as well as to remunerate the factors provided by the farmer. Following this approach, the opportunity costs of the factors provided by the olive grower were calculated and compared to the net income obtained by the farm.

For the calculation of the opportunity cost of land (OC_{Land}) it has been assumed that the best alternative use of owned land is its rental (Coppola et al. 2020; Hlavsa et al. 2020). Thus, for the estimation of this opportunity cost, the owned area of each farm was multiplied by the annual rental fee paid for olive groves in the region where the farm is located. This land rental value was taken from official statistics published by the MAPA. Mathematically (FADN code of the variables used shown in brackets when applicable):

$$OC_{Land} = [\text{ Total UAA (SE025)} - \text{ Rented UAA (SE030)}] \times \text{ Average annual rental fee in the region} \quad (1)$$

To calculate the opportunity cost of the labor provided by the olive grower and his/her family (OC_{Labor}), some authors use the average wage of the national agricultural sector (Ryan et al. 2016), or the average agricultural sector wage in the specific region in which the farm is located (Vrolijk et al. 2010). In our case, the opportunity cost of unpaid labor was estimated using the average annual wage paid for labor in the FADN sample of TF 37 farms. Thus, it was calculated using the following expression:

$$OC_{Labor} = \text{Unpaid labor input (SE015)} \times \text{ Average FADN TF 37 annual wage} \quad (2)$$

Finally, concerning the opportunity cost of non-land assets owned by the olive grower ($OC_{Capital}$), there are two common options for its calculation: on the basis of an annual cost similar to the interest rate of 10-year national government bonds (Vrolijk et al. 2010), or on the basis of an annual cost similar to a generic return of 5% (Hlavsa et al. 2020; Loughrey et al. 2022). Both options aim at replicating the cost of capital employed in low-risk investment alternatives. In the present study, we chose the first option since it better represents the dynamic of this opportunity cost by accounting for the evolution of the national economy as a whole. Therefore, the opportunity cost of non-land assets provided by the olive grower was calculated as follows:

$$\begin{aligned}\mathrm{OC}_{\mathrm{Capital}} = [\ & \text{Total fixed assets (SE441)} \\ & - \text{Long and medium term loans (SE490)} \\ & - \text{Land, permanent crops, and quotas (SE446)}] \\ & \times\ \text{Interest rate of 10-year national government bonds}\end{aligned} \tag{3}$$

Once the different opportunity costs had been estimated, it was possible to calculate the economic profit of the farms by deducting the overall opportunity costs from the net income. In addition, two other indicators were calculated to assess farms' viability (see Table 3). These indicators connect the net income generated on the farms with the opportunity cost of the factors provided by their owners, revealing the short-term (net income over opportunity cost of labor) and long-term viability (net income over total opportunity costs) of the farms (see Table 6 in Appendix 1).

The concept of farm *resilience* acknowledges the fact that farms' income is affected by several risks (Komarek et al. 2020). Notable examples in the case of olive farms include productive risks affecting yields (e.g., weather-related events such as droughts, frost, and hail, or biological events such as pests), market risks affecting farm sales revenue and input prices, and institutional risks (e.g., changes in agricultural policies). These risks generate uncertainty and economic instability for farmers (Darnhofer 2014), which justifies the increasing relevance of the analysis of agriculture systems' resilience (see, among others, Sneessens et al. 2019; Harkness et al. 2021). Following Meuwissen et al. (2019), resilience can be conceptualized as a structural capacity of farms that indicates their ability to minimize the impacts from changes in the global environment (climate, markets, technologies, etc.). Therefore, the analysis of this concept involves three subdimensions that characterize the farm's ability to cope with external pressures: robustness (stability of net income without making changes to the form of production), adaptability (capacity to slightly change the form of production–e.g., by changing the amount of inputs used) and transformability (capacity to radically change production–e.g., by changing the production technology or system). Nevertheless, the strategic and structural nature of the concept of transformability precludes its quantitative analysis using the economic and accounting data provided by the RECAN. For this reason, in this study, the analysis of resilience has been based exclusively on indicators that seek to quantify the robustness (CV of net income, net income resistance, and Shannon diversity index–SDI) and adaptability (flexibility of adjustment of specific costs, labor, and SDI) of olive farms. Table 6 in Appendix 1 shows the mathematical expression used to calculate each indicator selected for this dimension of economic performance.

The use of SDI for assessing farm resilience requires some explanation. This index quantifies farms' land use diversity by calculating the share of the various different crops and other land uses in the total farm area. As stated by Zampieri et al. (2020) and van der Lee et al. (2022), crop diversification helps to minimize agricultural risks by stabilizing farms' income, thus improving their robustness over time. This fact justifies the use of this indicator to assess farms' resilience in our case study.

The two properties (i.e., robustness and adaptability) and the indicators used to quantify farms' resilience must be considered as structural characteristics of the farms under analysis. In fact, all the selected resilience indicators were calculated only once, using data (net income, specific costs, labor, etc.) from a balanced panel of 212 olive farms for the whole 2014–2020 period (128 conventional and 84 organic olive farms). Therefore, the single value obtained for each indicator should be considered a constant value for farms over the seven years considered.

The last dimension of the economic performance analysis (*independence*) assesses farms' degree of economic dependence on CAP subsidies, comparing the amount of payment received to both revenue and net income (see Table 6 in Appendix 1).

Table 3 shows the average values of the selected economic performance indicators for the samples of conventional and organic olive farms in 2020, which can be considered an "average" season. Likewise, the values for the 2014 and 2018 seasons, representing "bad" and "good" seasons, respectively, are included in Appendix 2 (see Table 7).

Matching and average treatment effects estimation

The main objective of this work is to quantify the effect of organic farming (i.e., the treatment) on the farms' economic performance (i.e., outcomes), which can be defined as follows (Rubin 1974):

$$\tau_i = Y_i^1 - Y_i^0 \tag{4}$$

where Y_i^0 is the value of the outcome obtained by non-treated farm i and Y_i^1 is the value of the outcome obtained by farm i when the treatment is applied. Therefore, in our case, the effect of organic farming on the economic performance of a farm i can be estimated by simply subtracting the performance indicator obtained by this farm under organic farming (Y_i^1) from that obtained under conventional farming (Y_i^0). Here arises the main problem of estimating causal effects in observational studies: each subject (i.e., farm), at a specific moment in time, can either receive the treatment or not, but cannot belong at the same time to both treatment and control groups (Rosenbaum 2010). In other words, for our analysis, an olive farm can only be considered conventional or organic. Thus, for the same farm, we can only observe either Y_i^0 or Y_i^1, but not both outcomes. Therefore, to obtain the effect of organic farming on the economic performance of olive farming, we must estimate Y_i^1 for conventional farms (control group) and Y_i^0 for organic farms (treatment group); that is, we have to estimate the potential outcome that each subject would obtain if it were in the group to which it does not belong. Thus, the treatment effect on a subject i would be expressed as follows:

$$\tau_i = \begin{cases} Y_i^1 - \widehat{Y}_i^0 \; if \; T_i = 1 \\ \widehat{Y}_i^1 - Y_i^0 \; if \; T_i = 0 \end{cases} \tag{5}$$

where T classifies subjects in terms of treatment application ($T = 1$ for organic farms and $T = 0$ for conventional farms).

However, building a model to obtain a correct estimation of the potential unobserved outcomes requires that subjects belonging to the control and treatment groups (i.e., conventional and organic olive farms) are similar. Thus, we must assume the "strongly ignorable treatment assignment" condition, according to which the treatment is assigned to the subjects randomly and independently of the results they obtain (Rosenbaum and Rubin 1983; Imbens 2004).

In randomized experiments, the abovementioned condition is automatically assumed since the assignment of subjects to the treatment group is completely random (Rosenbaum 2010; Stuart 2010). However, this study is observational and non-randomized. Thus, it cannot be assumed that the assignment of subjects to the treatment group is random, nor can it be assumed that differences between observed and estimated outcomes for subjects in both groups are due exclusively to the treatment effect. This circumstance invalidates any comparative analysis of performance indicators based directly on their distributions in the analyzed samples, as is shown in the last two columns of Table 3 (and Table 7 included in Appendix 2) using Student's t-test for the group comparison. As pointed out in the introduction section, the way to overcome this problem is the use of matching methods, aimed at balancing the distribution of several observed covariates (e.g., farm size, farm location) between control and treated groups. These techniques match similar subjects from the control and the treated groups in order to achieve balanced covariate distributions between both matched groups and by so doing replicate a randomized experiment for the covariates considered (Stuart 2010; Ho et al. 2011).

From the multiple matching methods available (Stuart 2010), full matching (Hansen 2004) was selected for this research. This choice is justified for two reasons. First, this method uses all available information, assigning a "subclassification weight" (explained below) to each farm in the sample. Unlike the full matching technique, other matching methods—such as the exact, the nearest neighbor, or the optimal pair matching procedures—eliminate unmatched farms from the final sample (see Stuart 2010; Thoemmes and Kim 2011). Hence, the application of other matching methods to our case study would result in a much smaller number of matched farms, mainly due to the significant heterogeneity between olive farms, the relatively small number of organic farms in the samples, and the high number of covariates introduced into the analysis. By employing these techniques (i.e., eliminating unmatched farms from the final sample), we would lose significant amounts of valuable information available for the analysis.[2] Second, full matching, unlike the aforementioned conventional pair-matching methods, allows for the estimation of the average treatment effect (ATE) (Austin and Stuart 2017), the treatment effect choice for this study, as we explain later in this section.

In addition, following Rosenbaum and Rubin (1983), the propensity score (probability of treatment assignment for each subject) has been used as a distance criterion between subjects for matching. The propensity score has been estimated by logistic regression using the covariates considered for the analysis as explanatory variables. These methods have been implemented using the R package called "MatchIt" (Ho et al. 2011). It should be noted here that the use of full matching and the process of assigning weights to the observations may introduce a potential bias (Rosenbaum 2010). However, this possibility was ruled out by checking the propensity score distribution similarity between treated and control groups in every matched sample. This check ensured that the matched sample was correctly balanced in terms of the probability of treatment assignment for each farm, confirming the elimination of non-randomization bias for the selected covariates.

[2] In fact, this supposition was confirmed by the authors after testing the suitability of different matching methods for the analyzed samples.

Table 4 Average covariate values for organic and conventional farms in the RECAN for the year 2020 ("average" season)

Covariates	Organic farms ($n=130$)	Conventional farms ($n=246$)	Organic-conventional difference	
	Mean	Mean	Difference	$t/\chi2$ statistic
Olive grower's characteristics				
Age (years)	60.0	61.7	− 1.74	1.37
Gender (1 = female, 0 = male)	0.27	0.14	0.13	9.05**
Education (1 = academic, 0 = experience)	0.26	0.25	0.01	0.08
Full-time farmer (1 = yes, 0 = no)	0.27	0.48	− 0.21	15.6***
Farm characteristics				
Ownership type (1 = family, 0 = corporate)	0.85	0.90	− 0.04	1.63
Location (1 = Andalusia, 0 = rest of Spain)	0.88	0.83	0.05	1.72
Location in areas of natural constraints (1 = yes, 0 = no)	0.85	0.67	0.18	13.9***
Location altitude < 300m (1 = yes, 0 = no)	0.21	0.41	− 0.20	15.0***
Location altitude 300-600m (1 = yes, 0 = no)	0.70	0.32	0.38	50.4***
Product certification (1 = yes, 0 = no)	0.05	0.10	− 0.05	3.06
Utilized Agricultural Area, UAA (ha)	41.7	46.3	− 4.56	0.53
Irrigation area (%/UAA)	13.1	40.9	− 27.8	6.93***
Farm resources				
Land value (€/ha)	9337	12,443	− 3105	2.97**
Family labor input (%/total labor)	55.8	59.5	− 3.66	1.15
Production intensity (€/ha)	482	641	− 159	4.77***
Characteristics of the region				
GDP per capita (€)	18,293	18,622	− 329	1.31
Total organic area (%/regional UAA)	21.7	21.0	0.68	− 1.21
Olive organic area (%/regional olive UAA)	8.94	9.65	− 0.72	0.64

***, **, and * denote statistical significance at 0.1%, 1%, 5%, respectively

Matching methods are based on an appropriate selection of covariates. In our case, the covariates used in the matching process should guarantee, on the one hand, that organic farming adoption is completely random between compared farms (i.e., subjects) and, on the other hand, that matched conventional and organic farms have similar structural and productive characteristics. If these conditions are met, it can be assumed that the estimated differences between subjects for each economic performance indicator (i.e., outcomes) are due to the organic production system (i.e., treatment), and not to the influence of other underlying variables. The selection of covariates included in the analysis was based on an extensive literature review focusing on the factors that affect organic farming adoption (e.g., Parra-López and Calatrava-Requena 2005; Läpple and van Rensburg 2011; Sauer and Morrison Paul 2013; Rodríguez Pleguezuelo et al. 2018) and farms' structural characteristics that influence their economic performance (see, among others, Uematsu and Mishra 2012; Gillespie and Nehring 2013; Tey and Brindal 2015; Paul et al. 2017; Froehlich et al. 2018; Raimondo et al. 2021). Consequently, a total of 18 covariates were used to implement the selected matching method. These covariates included information about: a) olive growers' socio-demographic characteristics, b) structural characteristics of the farms, c) farm resources, and d) characteristics of the region in which the farms are located. Information on the covariates included in the analysis, as well as their averages in the compared samples for 2020 ("average" season), can be found in Table 4. The same information for 2014 ("bad" season) and 2018 ("good" season) years are included in Appendix 3 (see Table 8 and Table 9).

Once the probability of the treatment assignment has been estimated for each subject according to its covariates, full matching assigns each subject to a subclass according to its propensity score. For this purpose, an optimal number of subclasses is automatically created, such that the sum of the absolute distance between subjects within each subclass (i.e., the difference in their propensity scores) is minimal (Hansen 2004). Therefore, all subjects are assigned to a subclass and, on this basis, are assigned a "subclassification weight". Thus, after matching both samples under the condition of "ignorability in treatment assignment", a weighted general linear model using the subclassification weights was proposed. The general equation of the model can be expressed as shown:

$$Y = \beta_0 + \beta_1 T + \beta_2 \mathrm{COV}_1 + \beta_3 \mathrm{COV}_2 + \beta_4 \mathrm{COV}_3 \cdots + \varepsilon \tag{8}$$

where Y represents the outcomes to be estimated (economic performance variable), β_0 the intercept term of the linear model, and β_k the parameters of each of the explanatory variables, including the treatment assignment variable (T) and all the covariates (COV_j). To estimate the effect of the treatment on several outcomes (Y), as in this case, it is necessary to estimate the unobserved outcomes of each of the subjects by proposing a specific model for each Y (Ho et al. 2011).

There are three options for calculating the treatment effect on a sample: a) calculating the average treatment effect on the subjects of both the control and treatment groups (Average Treatment Effect, ATE), b) on the subjects of the control group (Average Treatment Effect for the non-treated Controls, ATC), and c) on the subjects of the treated group (Average Treatment Effect for the Treated, ATT) (for more detailed information see, among others, Imbens 2004; Imai et al. 2008). Given the main objective of this study, ATE was chosen.

Having estimated the unobserved results of all subjects for the corresponding Y, the average treatment effect on the whole matched sample (ATE) for each Y can be expressed as follows:

$$ATE = \frac{1}{N} \times \sum\nolimits_i (\tau_i | T) \tag{9}$$

Thus, the ATE was calculated as the sum of the individual treatment effect on the outcomes (Y) for all subjects i in the matched sample (τ_i), divided by the total number of subjects belonging to the matched sample (N).

Results and discussion

"Average" season (2020 year)

The main results obtained for each of the dimensions of economic performance analyzed in the 2020 season are presented in Table 5, allowing a comparison of the two production systems. These results suggest that the implementation of the organic production

Table 5 ATE estimates of organic production on the economic performance indicators for the years 2020 ("average" season), 2014 ("bad" season), and 2018 ("good" season)

Indicators	2020[a]		2014[b]		2018[c]	
	ATE	*p*-value	ATE	*p*-value	ATE	*p*-value
Productivity						
Land productivity (€/ha)	− 228	0.008**	− 158	0.197	− 199	0.028*
Labor productivity (€/AWU)	− 5259	0.102	3449	0.201	− 8632	0.044*
Capital productivity (%)	− 0.76	0.475	− 4.90	0.005**	− 2.52	0.041*
Profitability						
1. Sales revenue (€/ha)	− 228	0.008**	− 158	0.197	− 199	0.028*
2. CAP subsidies (€/ha)	82.9	0.018*	12.0	0.763	170.5	0.000**
CAP 1st pillar subsidies (€/ha)	− 66.0	0.024*	− 141	0.000***	− 73.2	0.009**
CAP 2nd pillar subsidies (€/ha)	145	0.000***	118	0.000***	232	0.000***
A. Total revenue (€/ha)	− 114	0.198	− 115	0.374	− 48.3	0.633
3. Intermediate consumption (€/ha)	33.4	0.227	− 41.9	0.084	− 22.1	0.383
B. Gross margin (€/ha)	− 156	0.056	− 120	0.355	7.07	0.940
4. Wages paid (€/ha)	− 54.3	0.022*	− 20.8	0.262	− 17.5	0.334
5. Rent paid (€/ha)	15.8	0.043*	− 22.0	0.003**	− 9.81	0.226
6. Depreciation (€/ha)	− 13.7	0.396	− 10.4	0.455	− 14.9	0.364
C. EBIT (€/ha)	− 99.4	0.240	− 12.1	0.926	58.6	0.516
D. EBT (€/ha)	− 99.3	0.240	− 5.59	0.966	60.1	0.504
E. Net income (€/ha)	− 104	0.218	8.87	0.946	56.9	0.528
ROA (%)	0.39	0.646	− 2.43	0.064	1.39	0.138
ROE (%)	0.32	0.716	− 1.30	0.326	1.33	0.157
Viability						
Total Opportunity Costs (TOC) (€/ha)	− 11.8	0.714	− 154	0.000***	− 5.42	0.844
Economic profit (€/ha)	− 120	0.175	112	0.405	30.5	0.744
Long-term econ. viability[d]	− 0.304	0.048*	− 0.077	0.733	− 0.086	0.594
Short-term econ. viability[d]	2.10	0.367	− 0.71	0.283	− 3.37	0.128
Resilience[e]						
CV of net income (%)	− 10.9	0.072				
Net income resistance (%)	24.9	0.607				
Shannon diversity index (SDI) mean[d]	0.025	0.315				
Specific costs adjustment flexibility (%)	63.3	0.000***				
Labor input adjustment flexibility (%)	− 1.89	0.450				
SDI adjustment flexibility (%)	0.99	0.016*				
Independence						
Revenue dependency (%)	9.00	0.000***	3.52	0.053	8.22	0.000***
Net income dependency (%)	57.9	0.544	348	0.179	17.7	0.090

***, **, and * denote statistical significance at 0.1%, 1%, 5%, respectively

[a] Year 2020: Matching 246 conventional farms with 130 organic farms

[b] Year 2014: Matching 203 conventional farms with 113 organic farms

[c] Year 2018: Matching 210 conventional farms with 113 organic farms

[d] Dimensionless variable

[e] Panel sample: Matching 128 conventional farms with 84 organic farms

system in olive groves leads to a decrease in *productivity*, mainly due to lower production intensity, as pointed out by several studies (see, among others, Tzouvelekas et al. 2001; Parra-López and Calatrava-Requena 2005; Guzmán et al. 2011). Nevertheless, the lower sales revenue of organic olive farms (−€228/ha) is largely offset by higher CAP subsidies (+€82.9/ha), as reported by Sgroi et al. (2015) and Iofrida et al. (2020). In any case, it is worth differentiating between subsidies coming from the first pillar of the CAP (direct payments supporting farm income) and subsidies from the second pillar (subsidies promoting agri-environmental schemes) (see Erjavec and Erjavec 2021). In this sense, it can be seen that payments from the first pillar of the CAP are lower for organic olive farms (−€66/ha), while subsidies from the second pillar are more favorable for organic olive farms: on average, €145/ha higher than for conventional olive farms.

These differences in CAP subsidies can be explained by considering how subsidies from these two pillars are granted to farmers. In Spain, direct payments from the first pillar, mainly the basic payment scheme (BPS), are based on individual payment entitlements, with highly heterogeneous values among farmers. The values of these payment entitlements depend on the coupled subsidies received by each farmer during the reference period (2000–2002), when the BPS was implemented for the first time, at which time they were ultimately linked to farms' productivity. This explains why olive farms that are potentially more productive, usually operating under conventional production, receive higher subsidies from the first pillar of the CAP. On the contrary, olive farms operating under organic production are generally located in less productive regions (e.g., mountainous areas or areas facing other natural constraints), where direct payments from the first pillar are much lower. Regarding the subsidies from the second pillar, it is obvious that only organic farms qualify for the agri-environmental scheme promoting organic farming. This explains why organic farms receive higher greening payments, reflecting the many benefits that this type of farming offers for the environment.

The overall greater economic support for organic farming from the CAP offsets production losses associated with this productive system, which clarifies why the analysis shows no significant differences between the total revenues obtained by conventional and organic olive growing.

Multiple studies evidence significant differences in *profitability* between conventional and organic olive farms, with most of them suggesting that the latter are more profitable (e.g., Sgroi et al. 2015; Berg et al. 2018; Iofrida et al. 2020).[3] Despite that, the results of this study do not support this claim, finding no treatment effect on general profitability indicators (EBIT, EBT, net income, ROA, or ROE) at a 5% statistical significance level. This result, however, is aligned with those obtained by other authors such as Uematsu and Mishra (2012), who compared the economic performance of conventional and organic crop farms in the United States.

Regarding the *viability* indicators, statistically significant differences are found in only one of them: long-term economic viability. The result for this indicator (-0.304) suggests that conventional farms are more viable, since they have a better capacity to compensate for all the opportunity costs incurred by the olive grower. However, no statistically

[3] In other agricultural sectors it has also been reported that the profitability of conventional farming is significantly different from that obtained under organic farming (e.g., Gillespie and Nehring 2013; Froehlich et al. 2018).

significant differences are found in indicators of total opportunity costs, economic benefit, and short-term viability. To the best of the authors' knowledge, no previous studies have analyzed differences in viability indicators between conventional and organic farming, underscoring the novelty of these results. The only example we can find is the study of Gillespie and Nehring (2013), who calculated the opportunity costs of unpaid labor in beef farms in the USA, without finding significant differences between conventional and organic production systems.

Regarding the *resilience* indicators, organic olive farms are shown to have greater flexibility in adjusting specific costs (+63.3%) and the SDI (+0.99%), suggesting that this production system is more capable of adapting to possible production and market shocks and are therefore more resilient than conventional olive farms. A similar conclusion was reached by Cabrera et al. (2013) in their comparison of alternative production systems in Andalusian olive farms.

As explained above, the results for the resilience indicators should be the same regardless of the season in question, since they are actually structural indicators (i.e., they have been calculated considering the whole period analyzed). Thus, the results for these indicators are only discussed for the average season, as explained above.

Focusing on the *independence* indicators, it can be observed that organic farms are more dependent on CAP subsidies (+9.0%). Indeed, as noted above, this circumstance is explained by the subsidies granted under the second pillar of the CAP, which are much higher in organic olive farms than in conventional olive farms.

"Bad" season (2014 year)

Table 5 also shows the comparison results when considering a "bad" season, based on 2014 data. For this season, there are no differences between the two production systems regarding land *productivity*. This finding contrasts with the results obtained for the average season, but is similar to the results of Volakakis et al. (2022) for the Greek olive sector. Again, differing from the results for the average season, capital productivity in the bad season is slightly lower for the organic olive farms (-4.9%).

Regarding the *profitability* indicators, there are no significant differences in sales revenue and current subsidies received by the two types of farms. In any case, similar to the average season results, organic farms receive lower payments from the first pillar of the CAP (−€141/ha) than conventional farms do, but more support from the second pillar of the CAP (+€118/ha). The results also indicate that, as in the average season, there are no significant differences in profitability between the two types of farms. Thus, in a bad season, the effect of the treatment on the general profitability indicators (EBIT, EBT, net income, ROA, or ROE) is statistically non-significant at a 5% level.

In the case of the *viability* indicators, no significant difference can be found between the two production systems. Differences are only observed in opportunity costs, which are lower (−€154/ha) for organic olive farms. Finally, contrary to the 2020 season, the results for 2014 do not suggest differences in the *independence* of the two types of olive farms.

"Good" season (2018 year)

With regard to the good season analyzed (the 2018 season in Table 5), results also show a lower land *productivity* of organic olive farms compared to conventional ones (−€199/ha), and the same is true of labor productivity and capital productivity (−€8632/AWU and − 2.52%, respectively). This is explained by the lower production intensity of organic farming, the productive limitations of which are particularly evident in cases of high yields and high olive oil prices.

Regarding *profitability* indicators, the conclusions that can be drawn are very similar to those for the 2020 season. Thus, the lower sales revenue from organic olive farming (−€199/ha) is offset by CAP subsidies (+ €171/ha), with the organic-conventional comparison revealing a negative difference for the payment received from the first pillar payments (−€73.2/ha) and an extremely positive difference for the subsidies granted under the second pillar (+ €232/ha). In this sense, there is no difference in total revenue between conventional and organic olive farms, a fact that supports the effectiveness of the CAP subsidies in promoting organic farming. Moreover, similar to the other seasons analyzed, no significant differences in profitability can be found between conventional and organic olive farms, since the effect of the treatment is not significant at a 5% level on any of the general profitability indicators (EBIT, EBT, net income, ROA, or ROE).

Regarding the *viability* indicators, there is no significant ATE, suggesting that there are no differences between the viability of organic and conventional olive farms in good seasons.

Finally, regarding the *independence* indicators, results are similar to those obtained for the average season, since organic olive farms are shown to be more dependent than conventional ones (+ 8.22%) due to the support received from the second pillar of the CAP.

Concluding remarks

The results of the empirical analysis have important implications for the efficient design of agricultural policy instruments aimed at promoting the expansion of organic olive farming. First, it is worth pointing out that the subsidies granted under the second pillar of the CAP were found to be the main factors explaining the progressive increase in the agricultural land under organic farming in recent years, since these subsidies offset the lower sales revenue (i.e., lower yields) obtained by organic olive farming. This leads us to conclude that subsidies for organic farming are generally an effective tool for encouraging an increase in the area devoted to organic agriculture. However, this conclusion needs to be supported by some additional comments.

CAP support (i.e., subsidies from the second pillar) has been a key factor in promoting the adoption of organic farming, especially in those olive groves with low levels of productivity under a conventional production system (e.g., olive groves in mountainous areas). Indeed, with a relatively small amount of agri-environmental subsidies, it has been possible to compensate for the drop in productivity resulting from the conversion to organic farming. This explains why organic olive farming has already been adopted in most areas in Spain where the olive groves are relatively less productive (average annual yield lower than 2000 kg of olives/ha).

Moreover, some insights into the different seasonal effects are also worth noting. In this sense, results show that the gap between organic and conventional olive farm productivity narrows in "bad" seasons but widens in "good" years. However, differences in terms of profitability or viability remain basically the same regardless of the scenario (i.e., "bad", "good", and "average" season). Thus, the main conclusions derived from annual results can be extended to the whole analyzed period. These findings confirm the general effectiveness of CAP agri-environmental subsidies in promoting the organic olive production system, as they adequately offset the profitability gap derived from this ecological transition.

Regarding sustainability, although this paper has focused on farms' economic performance, we cannot overlook the role of organic farming as a production system that generates significant positive social and environmental impacts: the enhancement of biodiversity and the quality of natural resources (soil and water), the reduction of non-renewable energy use and greenhouse gas emissions, or the support for rural development, among others (European Commission 2023). These benefits explain the reasoning behind the European Green Deal target of raising the agricultural area managed under organic production regimes to 25% by 2030. In this sense, the results showing the greater resilience of organic olive farms compared to conventional ones help justify public action to promote this production system. In sum, it has been demonstrated that fostering this production system in the olive sector could enhance farms' resilience while contributing to a more environmentally sustainable agriculture.

Nonetheless, the increase in the organic olive farming area required to meet the target set by the European Green Deal calls for more CAP support for organic farming. Higher subsidies can facilitate the gradual adoption of this production system in areas where conventional olive farming is more productive. However, if the current criterion for allocating subsidies to organic farming is maintained—that is, a payment per hectare uniformly granted to all farms signing this agri-environmental contract—the overall public expenditure needed for this policy would be considerably higher. This increase in the budget needed would contrast with the overcompensation received by those olive growers with less productive groves that have already converted to organic farming. For both these reasons, it is proposed that the subsidies should be allocated on the basis of the productivity losses experienced by the farms when adopting organic farming (i.e., the higher the current productivity, the greater the production losses after conversion, and the higher the subsidies to be received; and vice-versa). In this way, the increase in the organic olive farming area would be promoted more efficiently, compensating for the actual economic losses derived from the conversion to organic farming (i.e., lower production of private goods in favor of a higher provision of public goods), and preventing the generation of unjustified economic rents for olive growers with less productive olive farms.

In any case, as stated by Parra-López and Calatrava-Requena (2005) and Rodríguez Pleguezuelo et al. (2018), among others, the conversion to organic farming in the Spanish olive sector should also be promoted through the implementation of other complementary policies in addition to greater support from the second pillar of the CAP. Such policies could be aimed at (a) the development of training programs to raise olive growers' awareness of environmental conservation; (b) the incorporation of young farmers into the olive sector, contributing to the necessary generational change; and (c) encouraging the digitalization of agriculture, as a tool that would facilitate the conversion to organic olive farming and other eco-compatible production systems.

Moreover, relevant theoretical implications can be drawn from this study related to the application of matching methods when comparing two samples of farms. In this sense, the correct application of these techniques allows the bias caused by the influence of underlying variables (e.g., structural differences between conventional and organic farms) to be effectively minimized. Additionally, it has been evidenced that analyzing a long period (seven years in our case study) helps ensure a comprehensive assessment of farms' performance under different possible scenarios (e.g., weather conditions affecting crop yields) and enables the evaluation of resilience as a structural capacity of farms over time.

The main limitations of this study are related to the source of information used in the analysis. The RECAN does not collect certain data that would be valuable for the analysis, relating to outcomes such as olive yields (kg/ha) and covariates such as planting density (number of olive trees per hectare) or average farmland slope (%). In fact, if this information were available, a more accurate assessment of farms' economic performance could be performed. In any case, these data constraints do not invalidate the soundness and reliability of the results obtained.

Finally, stemming from this work, some proposals for future research are worth mentioning. First, extending the analysis to other dimensions of farms' sustainability (i.e., farms' environmental and social performance) would be helpful for a comprehensive assessment of farms' performance under different production systems. Moreover, this would allow an assessment of trade-offs between these farms' performance dimensions, which could lead to valuable insights to support sounder, more balanced policy instruments aiming at the ecological transition of the agricultural sector. Second, the analysis proposed could also be implemented to compare conventional farming with other alternative agricultural production systems that are growing in popularity, such as biodynamic production, a topic that has not been analyzed before. This is a knowledge gap that should be bridged to justify any public support for these environmentally-friendly production systems.

Appendix 1

See Table 6.

Table 6 Calculation formulas for each farm's economic performance indicator used in the analysis

Indicator (units)	Formula	RECAN data source codes
Productivity		
Land productivity (€/ha)	Total output / UAA	SE131 / SE025
Labor productivity (€/AWU)	Total output / Total labor	SE131 / SE010
Capital productivity (%)	Total output / Total assets	SE131 / SE436
Profitability		
1. Sales revenue (€/ha)	–	SE131
2. CAP subsidies (€/ha)	–	SE605
CAP 1st pillar subsidies (€/ha)	–	SE610 + SE615 + SE630
CAP 2nd pillar subsidies (€/ha)	–	SE624 + SE689
A. Total revenue (€/ha)	1 + 2	1 + 2
3. Intermediate consump. (€/ha)	–	SE275
B. Gross margin (€/ha)	A − 3	A − SE275
4. Wages paid (€/ha)	–	SE370
5. Rent paid (€/ha)	–	SE375
6. Depreciation (€/ha)	–	SE360
C. EBIT (€/ha)	B − 4 − 5 − 6	B − SE370−SE375−SE360
D. EBT (€/ha)	C − Interest paid (€/ha)	*C*−SE380
E. Net income (€//ha)	D − Taxes paid (€//ha)	*D*−SE390
ROA (%)	EBIT / Total assets	EBIT / SE436
ROE (%)	Net income / Equity	Net income / SE501
Viability		
Total opport. costs (€//ha)	$OC_{Land} + OC_{Labor} + OC_{Capital}$	–
Economic profit (€//ha)	Net income − TOC	–
Long-term econ. viability[a]	Net income / TOC	–
Short-term econ. viability[a]	Net income / OC_{Labor}	–
Resilience		
CV of net income (%)	$\frac{\sigma_{\text{Net income}_t}}{\overline{\text{Net income}_t}}$	–
Net income resistance (%)	$\text{Min}\left[\frac{\text{Net income}_t - \overline{\text{Net income}_t}}{\overline{\text{Net income}_t}}\,\forall t\right]$	–
Shannon div. index (SDI)[a]	$\overline{-\sum_i p_{i,t} \times \ln(p_{i,t})}$	p_i based on SE035, SE041, SE046, SE050, SE055, SE060, SE065, SE071, SE075
Specific costs adjus. flexibility (%)	$\overline{\left\lvert\frac{\text{Specif. costs}_t - \text{Specif. costs}_{t-1}}{\text{Specif. costs}_{t-1}}\right\rvert}$	$\overline{\left\lvert\frac{\text{SE281}_t - \text{SE281}_{t-1}}{\text{SE281}_{t-1}}\right\rvert}$
Labor input adjus. flexibility (%)	$\overline{\left\lvert\frac{\text{Total labor}_t - \text{Total labor}_{t-1}}{\text{Total labor}_{t-1}}\right\rvert}$	$\overline{\left\lvert\frac{\text{SE010}_t - \text{SE010}_{t-1}}{\text{SE010}_{t-1}}\right\rvert}$
SDI adjus. flexibility (%)	$\overline{\lvert SDI_t - SDI_{t-1}\rvert}$	–
Independence		
Revenue dependency (%)	Total CAP subsidies / Total revenue	SE605 / (SE131 + SE605)
Net income dependency (%)	Total CAP subsidies / Net income	SE605 / Net income

[a] Resilience indicators were calculated for a balanced panel of 212 olive farms for the period 2014–2020, including 128 conventional and 84 organic olive farms. The subscript *t* in these indicators refers to each of the years included in the analyzed period

Appendix 2

See Table 7.

Table 7 Average values of economic performance indicators for organic and conventional farms sampled by the RECAN for the years 2014 ("bad" season) and 2018 ("good" season)

Indicator	2014				2018			
	Organic farms ($n=113$)	Conven. farms ($n=203$)	Organic-conventional difference		Organic farms ($n=113$)	Conven. farms ($n=210$)	Organic-conventional difference	
	Mean	Mean	Diff	*t* statistic	Mean	Mean	Diff	*t* statistic
Productivity								
Land productivity (€/ha)	1112	1734	− 623	5.03***	1707	2299	-592	5.30***
Labor productivity (€/AWU)	24,072	30,153	−6080	2.31*	34,903	50,397	-15,494	3.93***
Capital productivity (%)	13.2	18.8	−5.66	3.56***	18.7	21.9	− 3.23	2.19*
Profitability								
1. Sales revenue (€/ha)	1112	1734	− 623	5.03***	1707	2299	− 592	5.30***
2. CAP subsidies (€/ha)	523	545	− 21.8	0.45	607	431	176	− 4.02***
CAP 1st pillar subsidies (€/ha)	309	516	− 207	5.36***	234	419	− 185	6.33***
CAP 2nd pillar subsidies (€/ha)	214	29.3	185	− 7.00***	373	11.9	361	− 11.9***
A. Total revenue (€/ha)	1635	2279	− 645	4.66***	2313	2730	− 417	3.31**
3. Intermed. consump. (€/ha)	505	708	− 203	4.96***	444	738	− 294	7.21***
B. Gross margin (€/ha)	1130	1571	− 442	3.60***	1869	1992	− 122	1.14
4. Wages paid (€/ha)	224	319	− 95.5	3.67***	262	363	− 101	3.69***
5. Rent paid (€/ha)	2.42	37.4	− 35.0	5.19***	13.9	39.7	− 25.7	3.54***
6. Depreciation (€/ha)	210	221	− 11.1	0.60	219	187	32.3	− 1.61
C. EBIT (€/ha)	694	994	− 300	2.66**	1374	1402	− 27.9	0.29
D. EBT (€/ha)	694	990	− 297	2.63**	1374	1400	− 26.2	0.27
E. Net income (€/ha)	673	968	− 295	2.62**	1356	1380	− 23.9	0.25
ROA (%)	8.52	10.8	− 2.33	2.09*	15.4	12.9	2.55	− 2.24*
ROE (%)	8.27	10.8	− 2.57	2.26*	15.2	12.8	2.38	− 2.08*
Viability								
Total Opportunity Costs (TOC) (€/ha)	860	911	− 51.2	0.91	820	780	39.7	− 0.97
Economic profit (€/ha)	− 187	57.2	− 244	1.97*	535	599	− 63.6	0.67
Long− term econ. viability[a]	0.90	1.40	− 0.50	2.61**	1.83	2.11	− 0.28	1.65

Table 7 (continued)

Indicator	2014				2018			
	Organic farms ($n = 113$)	Conven. farms ($n = 203$)	Organic-conventional difference		Organic farms ($n = 113$)	Conven. farms ($n = 210$)	Organic-conventional difference	
	Mean	Mean	Diff	*t* statistic	Mean	Mean	Diff	*t* statistic
Short− term econ. viability[a]	2.02	3.36	− 1.34	2.28*	5.19	10.3	− 5.12	2.17*
Independence								
Revenue dependency (%)	32.5	26.2	6.31	− 3.27**	26.5	16.1	10.4	− 6.69***
Net income dependency (%)	429	− 140	569	− 1.63**	47.1	27.8	19.3	− 2.10*

***, **, and * denote statistical significance at 0.1%, 1%, 5%, respectively

[a] Dimensionless variable

Appendix 3

See Tables 8 and 9.

Table 8 Average values of selected covariates for the organic and conventional farms sampled by the RECAN for the year 2014 ("bad" season)

Covariates	Organic farms ($n = 113$)	Conventional farms ($n = 203$)	Organic-conventional difference	
	Mean	Mean	Difference	t/χ2 statistic
Olive grower's characteristics				
Age (years)	54.8	59.4	− 4.59	3.98***
Gender (1 = female, 0 = male)	0.30	0.11	0.19	18.5**
Education (1 = academic, 0 = experience)	0.13	0.06	0.07	5.04*
Full-time farmer (1 = yes, 0 = no)	0.53	0.62	− 0.09	2.41
Farm characteristics				
Ownership type (1 = family, 0 = corporate)	0.87	0.93	− 0.06	3.54
Location (1 = Andalusia, 0 = rest of Spain)	0.94	0.75	0.18	16.7***
Location in areas of natural constraints (1 = yes, 0 = no)	0.95	0.66	0.29	33.0***
Location altitude < 300m (1 = yes, 0 = no)	0.08	0.28	− 0.20	17.8***
Location altitude 300-600m (1 = yes, 0 = no)	0.85	0.40	0.45	59.8***
Product certification (1 = yes, 0 = no)	0.03	0.16	− 0.14	13.3***
Utilized Agricultural Area, UAA (ha)	35.1	34.3	0.83	− 0.20
Irrigation area (%/UAA)	10.6	33.3	− 22.7	5.68***
Farm resources				
Land value (€/ha)	6371	11,737	− 5367	5.76***
Family labor input (%/total labor)	64.8	63.4	1.40	− 0.59
Production intensity (€/ha)	495	580	− 84.8	2.59*
Characteristics of the region				
GDP per capita (€)	17,978	19,209	− 1231	4.44***
Total organic area (%/regional UAA)	22.4	20.5	1.89	− 3.46***
Olive organic area (%/regional olive UAA)	7.45	10.6	− 3.17	2.98**

***, **, and * denote statistical significance at 0.1%, 1%, 5%, respectively

Table 9 Average values of selected covariates for the organic and conventional farms sampled by the RECAN for the year 2018 ("good" season)

Covariates	Organic farms (n = 113)	Conventional farms (n = 210)	Organic-conventional difference	
	Mean	Mean	Difference	t/χ2 statistic
Olive grower's characteristics				
Age (years)	57.9	61.7	− 3.81	2.90**
Gender (1 = female, 0 = male)	0.32	0.15	0.17	13.1***
Education (1 = academic, 0 = experience)	0.23	0.18	0.05	1.36
Full-time farmer (1 = yes, 0 = no)	0.52	0.50	0.02	0.14
Farm characteristics				
Ownership type (1 = family, 0 = corporate)	0.83	0.88	− 0.04	1.20
Location (1 = Andalusia, 0 = rest of Spain)	0.88	0.83	0.04	1.04
Location in areas of natural constraints (1 = yes, 0 = no)	0.84	0.71	0.13	6.84**
Location altitude < 300m (1 = yes, 0 = no)	0.18	0.36	− 0.18	11.5***
Location altitude 300-600m (1 = yes, 0 = no)	0.73	0.37	0.36	38.7
Product certification (1 = yes, 0 = no)	0.04	0.11	− 0.08	5.77
Utilized Agricultural Area, UAA (ha)	35.2	50.8	− 15.6	2.12
Irrigation area (%/UAA)	12.0	37.0	− 25.0	6.03
Farm resources				
Land value (€/ha)	8,578	12,780	− 4,202	3.60
Family labor input (%/total labor)	61.4	56.0	5.49	− 1.84
Production intensity (€/ha)	406	575	− 169	5.94
Characteristics of the region				
GDP per capita (€)	18,281	18,446	− 165	0.62
Total organic area (%/regional UAA)	21.6	20.9	0.72	− 1.18
Olive organic area (%/regional olive UAA)	9.22	9.36	− 0.14	0.12

***, **, and * denote statistical significance at 0.1%, 1%, 5%, respectively

Abbreviations

ATC	Average Treatment Effect for the non-treated Controls
ATE	Average Treatment Effect
ATT	Average Treatment Effect for the Treated
AWU	Annual Work Unit
BPS	Basic Payment Scheme
CAP	Common Agricultural Policy
CV	Coefficient of Variation
EBIT	Earnings Before Interest and Taxes
EBT	Earnings Before Taxes
EU	European Union
FADN	Farm Accountancy Data Network
FAO	Food and Agriculture Organization of the United Nations
FNI	Farm Net Income
FNVA	Farm Net Value Added
GDP	Gross Domestic Product
GFI	Gross Farm Income
IFOAM	International Federation of Organic Agriculture Movements
INE	Instituto Nacional de Estadística (National Statistics Institute)
MAPA	Ministerio de Agricultura, Pesca y Alimentación (Ministry of Agriculture, Fisheries, and Food)
OC	Opportunity Costs
RECAN	Red Contable Agraria Nacional (Spanish Farm Accountancy Data Network)
ROA	Return On Assets
ROE	Return On Equity
SDI	Shannon Diversity Index
TF	Type of Farming
TOC	Total Opportunity Costs
UAA	Utilized Agricultural Area

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JMG: Methodology, Formal Analysis, Writing—Original Draft, Visualization; JAGL: Conceptualization, Methodology, Writing—Review and Editing, Funding acquisition; MA: Conceptualization, Methodology, Formal Analysis, Writing—Review and Editing. All authors revised and approved the final manuscript.

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Availability of data and materials
The data supporting this study's findings are available from the corresponding author upon reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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