Article

Organic Farming Increases the Technical Efficiency of Olive Farms in Italy

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Abstract: While there is growing recognition of the positive role played by organic farming in the reduction of the negative externalities due to conventional agriculture, there is uncertainty about the effect of the latter on the economic performance of the farms. In this scenario, the present paper aims at investigating the effect of organic farming on technical efficiency in Italian olive farms. A cross-section dataset was analyzed through the stochastic frontier function, where the adoption of organic farming was explicitly modeled. Then, to obtain an unbiased estimate of the impact of organic farming on technical efficiency, a propensity score matching method was implemented. The findings reveal that organic farming increases technical efficiency in Italian olive farms by approximately 10%. The highest impact of organic farming is observed in small farms. As for the propensity to become organic, we found that the production and the direct sales of a higher quality of gross marketable output, as well as the intensity of labor and machines, increase the probability to adopt organic farming. Conversely, farm localization, the availability of family labor, and financial capital discourage conversion to the organic farming system.

Keywords: organic agriculture; stochastic frontier function; propensity score matching; FADN; olive farms

1. Introduction

For decades to come, agriculture has imposed many negative externalities upon society, through the overuse of land and water resources, biodiversity loss, soil erosion, and the unsustainable use of pesticides [1,2]. The external costs of conventional agriculture raise important challenges to both the scientific community and policymakers, especially with regards to identifying more effective management practices for reducing negative externalities [3] while increasing the supply of public goods [4–6]. Accordingly, the general interest in alternative farming systems (AFSs) is increasing [7–9] because AFSs improve the ecological, social, and economic dimensions of sustainability [8,10]. Organic agriculture represents an effective practice to use natural resources in a more environmental-friendly way as it involves dependence on self-regulating ecological or biological processes and renewable resources [11]. Organic agriculture is the main AFS adopted in the world [12]. Notwithstanding, while there is growing social recognition of the positive role played by this type of farming in the conservation of natural resources and the reduction or elimination of the negative externalities of conventional agriculture, the conversion to organic farming is still scarce [7]. Accordingly, despite that organic food consumption has risen in many countries during the past decades [13], the organic production comes from

only 1% of the global agricultural land [12], motivating the European Commission to increase organic farming through the Farm to Fork Strategy [14]. A recent study from Home and co-authors [7] highlighted some of the main barriers to farmers' conversion. The study found that external, technical production, social, and personal factors influence the decision of whether to convert to organic production [7]. Certification (e.g., organic) is also considered a high-entry barrier for many small-scale farmers [15–17]. Several studies examined the impact of certification on the return on investment, yields, selling prices, farming practices, or welfare measures such as farm income [18–21]. Most researchers found modest positive impacts of different certifications on economic welfare [19,21–24]. Other researchers have been rather skeptical about the ability of certification to increase farmers' wellbeing, as it affects revenue only marginally while involving high restrictions and high costs [24–26]. Moreover, several scientists found that protectionism through the certification system tends to generate technical inefficiencies, and thus productivity losses [27,28], as it reduces technical choices for organic farming. However, according to other researchers, restrictions on production inputs forcing organic farmers to be more cautious with input use thus reduce production costs [29,30].

Based on what has been said so far, the present study analyses cross-section Italian Farm Accountancy Data Network (FADN) to investigate the effect of certified organic agriculture on technical efficiency (TE) in Italian olive farms. The Mediterranean basin is the largest world area having specific climatic conditions suitable for olive cultivation [31]. The Mediterranean area is the geographic location in which, more than in others, olive growing is a significant source of income and employment for rural populations both in European countries (such as Spain, Italy, Greece, and Portugal) and in non-European ones (Tunisia, Turkey, and Syria) [31]. Italy represents the second-largest producer of olive oil, with 570,000 tons (about 20% of world production), and the first consumer, with 610,000 tons (19.8% of consumption worldwide) [32,33]. According to the Italian Institute of Statistics (ISTAT) [34], the Italian olive area amounts to 1.17 million hectares and involves 902,075 farms (56% of total Italian farms). Olive farming is mainly concentrated in the Southern regions, Apulia, Calabria, and Sicily. Despite that, in Italy, organic olive growing is the most widespread organic tree cultivation [35], only 20% of the national olive area is devoted to organic production in 2018 [36]. To the best of our knowledge, this is the first research that investigates the organic certification effect on the technical efficiency of olive farms. The remainder of the paper is organized as follows. The research question of the study is pointed out in Section 2. In Section 3, the methodology is explained followed by data description. Section 4 presents the results, while the last section (Section 5) concludes.

2. Theoretical Background

Over the last decades, policymakers have been increasing their interest in the economic and environmental performances of production systems to design effective policies. Accordingly, several studies have compared technical efficiency between conventional and organic farming systems [37–39]. Technical efficiency (TE) assesses the ability of a farm to obtain maximum outputs given a limited set of inputs (called output-oriented) or the ability to use the minimum amount of inputs given a finite level of outputs (called input-oriented) [40–42]. The literature is not unanimous about the technical efficiency differences among organic and conventional farms. In a recent review, Lakner and Breustedt [43] pointed out that organic farms mainly achieve lower technical efficiency—roughly 4 percent—than conventional farms [29,40,44]. Besides, Flubacher [36], who compared the technical efficiency of organic and conventional dairy farms in the Swiss mountain region, highlights similar results. Conversely, some researchers revealed that the technical efficiency attained by organic farms is higher than that of conventional ones [45,46].

Researchers also disagree about the effects caused by converting conventional farms to organic farms [47]. According to some of them, organic certification has a positive effect on farmers' income [48–50]. The organic farming system leads to specific consequences,

such as (i) the reduction of production costs owing to lower use of pesticides and fertilizers, (ii) the increase of income through the price premium given by consumers [51–53], and (iii) the economic payment and the offset of crop yields [54]. For instance, Mansoori and colleagues [55] found that, in rice production, organic practices achieve lower costs of production than conventional farms. Unlike previous authors, some others revealed that organic farming certification negatively affects farm profitability [56,57] owing to specific aspects: (i) the prohibition of using chemicals increases the potential production risk; (ii) a higher price risk is also highlighted as the demand for organic products is poor or sometimes unvoiced [57]; (iii) a higher labor demand, especially for organic orchards [11]; and (iv) a higher machinery use and changes in production practices [58]. Moreover, the increase in producer price and the economic subsidies might be not sufficient to compensate for the certification costs [59]. According to Zhang and colleagues [57], the net income per hectare was 25% lower in organic soybean farms than in the conventional system, while Froehlich and colleagues [60] assessed the Brazilian organic producers' profits to be around 7–10% lower than those of the conventional farms.

The occurred dichotomy is the main driver of the current study, which aims to assess the effect of organic certification on farm technical efficiency in Italian olive farms. In particular, this research aims to identify to what extent organic certification may influence the technical efficiency of Italian olive farms. To reach this purpose, we firstly estimate technical efficiency through the parametric approach, where external factors (e.g., organic certification) have been explicitly modeled. Then, once scores are obtained, the impact of the organic certification on technical efficiency is identified in a quasi-experimental approach by employing the propensity score matching (PSM) method.

3. Methods

3.1. Stochastic Frontier Analysis

Technical efficiency (TE) is widely investigated for olive farms [27,61–63]. The measure of TE was proposed for the first time by Farrell [64], who compared the observed output to the best production output, given a specific quantity of input. Based on this concept, several approaches were developed to estimate TE, which can be grouped into two main categories: the parametric and the non-parametric methods [40,65]. The former assume a defined functional form of the production function and frequently include the stochastic frontier production (SFP) approach [66,67]. Conversely, the non-parametric methods do not assume a specific functional form, as in the data envelopment analysis (DEA) approach. Notwithstanding the last one seems a more flexible and generalizable method, as it does not define a priori a specific function of production, the main deficiency is its deterministic nature. Specifically, the DEA approach does not allow distinguishing between inefficiency due to technical inefficiency and accidental disturbance [65,68], but all deviations from the production frontier are related to technical inefficiency. Thus, according to Battese and Coelli [69], a non-parametric model is inappropriate for several agro-economic studies because DEA does not indicate if inefficiency is due to entrepreneur's management or if it depends on contextual variables, such as environmental characteristics. Unlike the DEA model, the SFP model—adopted in the current study—includes two error components: one representing the stochastic effect related to statistical noise (v) and the other related to technical inefficiency of the farms (u). In particular, by following Battese and Coelli [69], we have tested several specifications that differ for the functional form (Cobb–Douglas or Translog) and for including (or not) the environmental factors in the inefficiency term(u) or directly in the production function (Table 1).

Table 1. Model selection.

Model	Functional Forms	Inclusion of Env. Factors in the Production Function	Inclusion of Env. Factors in the Inefficiency Term	Log-likelihood	Number of Parameters	AIC	BIC
1	Cobb–Douglas	NO	NO	−306.2	7	626.3	653.5
2	Translog	NO	NO	−299.6	11	621.2	663.8
3	Cobb–Douglas	NO	YES	−281.9	12	587.7	634.2
4	Translog	NO	YES	−270.7	16	573.4	635.3
5	Translog	YES	NO	−275.0	17	584.0	649.8
6	Cobb–Douglas	YES	NO	−285.3	13	596.7	647.0
7	Cobb–Douglas	YES	YES	−278.2	18	592.5	662.2
8	Translog	YES	YES	−266.4	22	576.7	661.9

The Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC) suggest including the environmental factors only in the inefficiency term (model 3 and 4), while they do not provide a clear indication on the functional form. Thus, the following Cobb–Douglas production function was selected for the parsimony of parameters, with the assumption of constant returns to scale (Equation 1):

$$\ln y_i = \beta_0 + \sum_{k=1}^{3} \beta_k \ln x_{k,i} + v_i - u_i \tag{1}$$

$$i = 1,\ldots, 355$$

where y_i is the observed output of the i-th firm, $x_{k,i}$ represents the value of k-th input used by the firm (working capital, land capital, and labor), and β_0 and the β_k are parameters to be estimated. The v_i is an error term with zero mean and variance σ_v^2, and u_i is an independent random term accounting for technical inefficiency in production.

Following Battese and Coelli [69] and Coelli and colleagues [70], the predictor of TE involves the conditional expectation of exp (−u_i), given the random variable ε_i. Accordingly, TE is defined as follow (Equation 2):

$$TE_i = E [\exp (u_i) | \varepsilon_i] \tag{2}$$

The defined frontier model does not account for the possibility that different environmental conditions may influence the different levels of farms' technical efficiency. However, it has been shown that environmental conditions may affect (i) the shape of production technology as well as (ii) the TE of the firm [70]. According to Battese and Coelli [69], environmental factors directly affect the degree of technical inefficiency, thus the environmental factors would be modeled to assess the inefficiency term (u_i). In other words, the environmental factors do not affect the technology endowment, but they may influence the distance that separates each firm from the best practice function.

As a consequence, the inefficiency term (u_i) obtained by the truncation of the normal distribution with mean $\delta_m z_{m,i}$ and variance σ^2 can be expressed as a function of a vector ($z_{m,i}$) of M environmental and farm characteristics, while δ_m are the parameters to be estimated (Equation 3).

$$u_i \sim N^+\left(\sum_{m=1}^{M} \delta_m z_{m,i}, \sigma^2 \right) \tag{3}$$

$$i = 1,\ldots, 355$$

This specification assumes that the z term may influence the inefficiency of the farm without implying a real change in the technology.

Therefore, Equation (1) becomes the following:

$$\ln y_i = \beta_0 + \sum_{k=1}^{3} \beta_k \ln x_{k,i} + v_i - \left(\sum_{m=1}^{M} \delta_m z_{m,i}, \sigma^2 \right) \tag{4}$$

$$i = 1,\ldots, 355$$

where $\ln y_i$ is the logarithmic of the gross marketable production, the output of the stochastic frontier function (Equation 4). The term $\ln x_{k,i}$ includes the standard inputs of production, such as land capital, working capital, and labor, while $z_{m,i}$ refers to the environmental and farm characteristics. Based on previous studies, this work includes in the z_m term the presence of organic certification [23–25], the altimetry [71], as well as the geographic area [72] and the diversification of production [43].

3.2. Treatment Effect of Organic Certification

Equation (4) allows us to assess the TE of both organic and conventional farms. More precisely, significant differences in TE between organic and conventional farms could be associated with the certification. However, we are not able to properly identify the effect of organic certification on TE because sample selection bias or endogeneity problems may arise. The former occurs if conventional farms are systematically different from those organic (for instance, being larger), thus, consequently, the comparison is biased by other structural differences. The endogeneity occurs when there are specific motivations for farmers to adopt organic certifications that might also be related to the outcome of interest, basically, the technical efficiency. To overcome these problems, a quasi-experimental approach should be followed. The key advantage of quasi-experimental studies (over non-experimental methods) is the possibility to artificially adjust (i.e., basically through statistical procedures) the non-randomness of both control and treatment groups to make them comparable for the observing characteristics. Only after this adjustment, the treatment effect can be measured as the difference of mean outcomes [73]. More in detail, to reduce the estimation bias resulting from the comparison between two groups (control and treated), a propensity score matching (PSM) was implemented. We keep the "treated" and "control" terms of experimental studies and we intend, for "treated", the organic farms, and for the "control" group, or untreated, the conventional ones. If the status of being organic ($O_i = 1$) stochastically depends on a set of observable characteristics, meaning that it is not randomly assigned, the propensity score can be implemented as a measure of conditional probability (Equation 5) of being organic upon the observed variables, s, namely farm and farmer characteristics (reported in Table 2):

$$p(s_i) = Pr[O_i = 1 \mid s_i]$$

$$i = 1,\ldots, 355$$

(5)

Table 2. Descriptive statistics of variables for organic and conventional farms.

Variable	Variable Description	All Sample (obs.355)		Organic Farms (obs.103)	Conventional Farms (obs.252)
		Mean	Std. Dev.	Mean	Mean
GMO	Economic value of gross marketable output (GMO)	81,367.3	118,783.5	74,182.15	84,304.12
Added_value (€)	Farm net value added	68,643.81	105,204.1	62,958	70,967.77
Working_Cap	Economic value of circulating agricultural capital	615.782	912.397	521.47	654.33
Mec_value (€)	Economic value of machines	19,450.48	30,483.94	14,702.25	21,391.22
Capes_UAA (€/ha)	Ratio between the circulating agricultural capital and UAA	1454.38	2685.18	1051.79	1618.93
Mecc_UAA (€/ha)	Ratio between mechanic value and UAA	1433.75	2614.26	1047.54	1591.61
Labour	Economic value of labour	40,687.1	45,902.38	37,742.26	41,890.78
Hours of labor	Total hours of labour	4238.24	4781.5	3931.49	4363.62
Lab_prod (€/hour)	Ratio between GMO and hours of labor	17.99	10.41	18.58	17.75
Activity (hours/ha)	Ratio between hours of labor and UAA	324.54	346.77	267.99	347.66
Labf (hours_fam/ha)	Ratio between hours of family labour and UAA	0.09	0.08	0.07	0.1
Land_Cap	Economic value of land capital	7400.55	11,884.64	7227.24	7471.39
Land_prod (€/ha)	Ratio between GMO and UAA	4748.63	3564.74	4174.31	4983.37
UAA (ha)	Used agricultural area (UAA)	21.56	31.55	21.08	21.75

GMO_quality (1 = yes; 0 = no)	Gross marketable output obtained from quality products	0.05	N.A.	0.1	0.04
Short_sc (1 = yes; 0 = no)	Short supply chain	0.1	N.A.	0.15	0.09
Diversified activities	Presence of complementary activities (1 = yes; 0 = no)	0.1	N.A.	0.12	0.09
Gender	(1 = female; 0 = male)	0.34	N.A.	0.32	0.34
Young	(1 = yes; 0 = no)	0.17	N.A.	0.19	0.16
Altimetry classification	(1 = mountain 2 = hill 3 = plain)	2.13	N.A.	2.1	2.14
Geographic area_1	(1 = south and island; 0 = otherwise)	0.8	N.A.	0.86	0.77
Geographic area_2	(1 = north; 0 = otherwise)	0.05	N.A.	0	0.07
Geographic area_3	(1 = center; 0 = otherwise)	0.15	N.A.	0.14	0.15

N.A. not applicable; in bold, variables included in the stochastic frontier model.

Then, to analyze factors that may affect the probability of observing farms being organic, p(s_i), the following discrete choice model is implemented (Equation 6):

$$Pr(Y_i{=}1) = \Phi(\alpha + \beta W_i + \gamma T_i + \eta_i)$$

$$i = 1,\ldots, 355$$

(6)

where Y_i is the observable binary variable of farms, while Φ is the cumulative distribution function of the standardised normal variable. W_i is a vector of structural characteristics of the i-th farm and the T_i term is a vector of socio-demographics characteristics of the i-th farmer. Finally, η_i is the error component.

Once a propensity score estimation is computed, the next step is to match the treated (organic farms) to a control group (conventional farms) based on the estimated propensity score [74,75]. Only those farms having a similar propensity of being organic were compared. To do this, we estimated the average effect of treatment on the treated (ATT) by the stratification matching and the nearest-neighbour matching methods (Equation 7).

$$ATT = E[\Delta Y_i \,|\, p(s_i), O_i = 1]$$

$$i = 1,\ldots, 355$$

(7)

The stratification matching method consists of dividing the range of variation of the propensity score in intervals such that, within each interval, treated and control units have on average the same propensity score. Then, within each interval in which both treated and control farms are present, the difference between the average outcomes of the treated and the control is computed. Finally, the ATT of interest is obtained as an average of the ATT of each block with weights given by the distribution of treated units across blocks. The main weakness of this method is that it discards observations in blocks wherein either treated or control units are absent. An alternative way to match treated and control units, which consists of taking each treated unit and searching for the control unit with the closest propensity score, is the nearest neighbour matching method. In this case, a control unit can be the best match for more than one treated unit. Once each treated unit is matched with a control unit, the difference between the outcome of the treated units and the outcome of the matched control units is computed. The ATT of interest is thus obtained by averaging these differences.

3.3. Data Description

The FADN database is used for conducting the investigation. FADN represents the official EU source of micro-data for understanding the impact of agricultural policies. It contains around 1,000 variables for monitoring farms' income and business activities, covering approximately overall 10,000 Italian farms, and it is representative of the national population of farms [76]. Our analysis includes data on Italian olive farms from 2015. Regarding this production, the sample includes 355 olive farms, of which 29% are organic (n = 103) and the remaining 71% are conventional (n = 252). Table 1 shows the descriptive statistics of the main economic and structural characteristics of both organic and conventional farms.

4. Results

4.1. Technical Efficiency Estimates

The estimated coefficients of the stochastic frontier model are presented in Table 3. Coefficients have the expected signs as all inputs of production included in the model, such as working capital, land capital, and labor, are positively associated with the gross marketable output (GMO) of farms. The estimated coefficients of the Cobb–Douglas functional form represent input elasticities, showing the greatest elasticity (+0.98) for labor. As for the inefficiency measure (the U term in Table 3), all environmental variables are significant. In particular, organic certification is negatively associated (–1.01) with the technical inefficiency error component. This provides some evidence that organic certification may increase the technical efficiency (TE) of the farm. Furthermore, farms located in hill or plain areas show a negative impact on the farm technical inefficiency error component (–0.84 and –1.26, respectively), thus olive farms located in mountain areas seem less efficient than those located in hill or plain areas. A negative association with the technical inefficiency error component is also shown by farms located in Northern Italy, but this is not significant. Conversely, a positive and significant impact (+1.082) on inefficiency is revealed in the central regions, meaning that olive farms located in Central Italy seem less efficient than those located in the southern regions. The increase of technical inefficiency of the farm is also due to the presence of activities complementary to the agricultural production. Indeed, our findings show that the diversified activities at the farm level may increase technical inefficiency by 1.23.

Table 3. Coefficient estimates of the stochastic frontier analysis.

Dep.var: ln (GMO)	Coef.	Std. Err.	*p*-Value
Frontier			
ln (working_cap)	0.044	0.017	0.009***
ln (land_cap)	0.125	0.022	0.000***
ln (labour)	0.980	0.044	0.000***
Cons	−0.109	0.411	0.790
U			
Organic certification	−1.011	0.391	0.010**
Geographic area (north)	−3.690	3.311	0.265
Geographic area (center)	1.082	0.299	0.000***
Diversified activities	1.234	0.327	0.000***
Altimetry classification (hill)	−0.842	0.366	0.021**
Altimetry classification (plain)	−1.258	0.516	0.015**
Usigma			
Cons	−0.299	0.214	0.163
Vsigma			
Cons	−1.948	0.168	0.000***

Obs. = 355; Wald chi^2 = 930 (*p*-value < 0.001); * frontier test (M3T): 30.39, (*p*-value < 0.001). *p*-value < 0.1; ** *p*-value < 0.05; *** *p*-value < 0.01.

The following figure (Figure 1) illustrates the distribution of TE (θ) of both organic and conventional farms. The values of θ give information about the distance from the data point to the production frontier assuming values from "0" to "1", where "0" means the lowest value of farm TE, while "1" is the maximum value of TE. Even if the distribution functions of TE for the two groups of farms are similar, the average value of θ for organic farms is 0.716, while it is equal to 0.640 for conventional farms. Table 4 shows the average percentage differences in TE between organic and conventional farms grouped by macro-areas and by the size of the farms in terms of used agricultural area (UAA). The highest average value of TE is achieved in conventional farms located in Northern Italy (0.863), while the highest value of TE in organic farms is achieved in farms located in Southern Italy. However, it should be highlighted that there are no organic olive farms in Northern Italy.
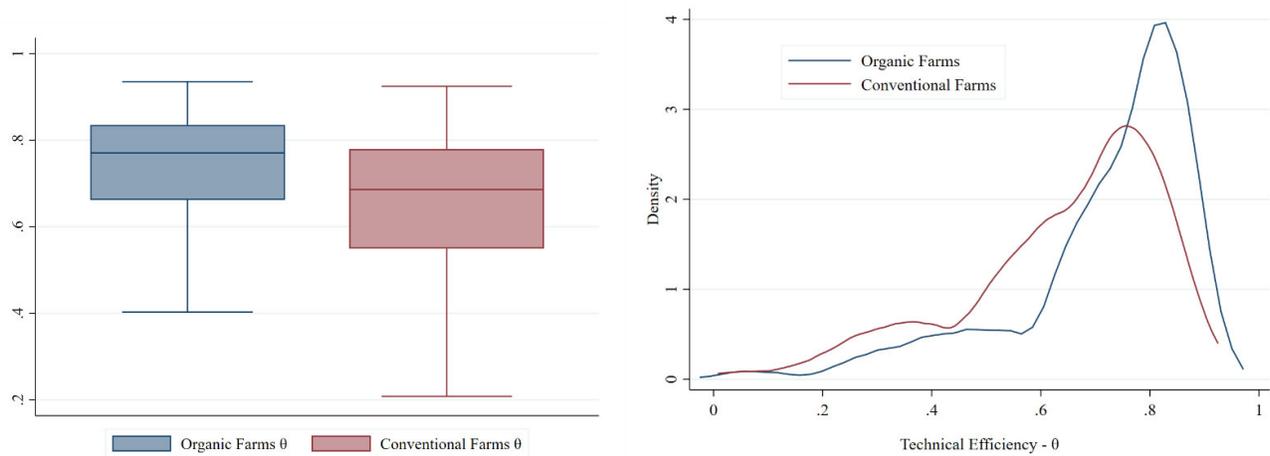
Figure 1. Technical efficiency parameter (θ).

Table 4. Descriptive statistics and average values of technical efficiency (TE) by macro areas.

Description	Area	Average θ	Obs
	South and Islands	0.751	89
Organic	Center	0.504	14
	North	N.A.	0
	South and Islands	0.671	195
Conventional	Center	0.462	39
	North	0.863	18

N.A., not applicable.

Moreover, the findings emphasized that the greatest differences in TE values are mainly observed in small farms—those with less than five hectares—and especially in farms located in Central Italy. Indeed, the average percentage differences in TE for organic farms is more than 28% in small farms located in Central Italy, followed by farms located in the South and in North Italy, where the percentage differences in TE are 15.6% and 14.9%, respectively (Table 5).

Table 5. Average percentage differences in TE for organic olive farms by macro areas and by UAA.

Area	Class UAA	Δθ (%)	Std. Dev.	Frequency	Distribution
	<5 ha	15.6	5.39	31	11%
	5–15 ha	14.5	7.77	146	51%
South and Islands	15–40 ha	9.9	6.82	71	25%
	>40 ha	9.9	7.22	36	13%
	Total			284	100%
	<5 ha	28.4	1.63	4	8%
	5–15 ha	23.7	8.32	24	45%
Center	15–40 ha	21.1	8.34	14	26%
	>40 ha	16.8	7.84	11	21%
	Total			53	100%
	<5 ha	14.9	9.50	9	50%
North	5–15 ha	11.7	8.35	9	50%
	Total			18	100%

4.2. Propensity Score and ATT Estimates

The previous paragraph shows that, on average, olive farms with organic certification seem more efficient than those without organic certification. However, a propensity score matching needs to be performed to correctly attribute those observed differences to the presence of the organic certification, or to identify the treatment effect of the organic certification. More specifically, the propensity score was estimated using a Probit model including both structural and economic characteristics of farms as well as farmers' socio-demographic profile. The dependent variable assumes a value of 1 if the farm was organically certified and 0 otherwise. The variables included in the model closely correspond to those previously recognized as notably different among the two groups of farms. Moreover, the Probit model considers those characteristics that have been identified by previous literature to be associated with the organic certification adoption [23–25,77–79].

The results indicate that the propensity for a farm to adopt organic certification is positively influenced by the added value and the overall mechanic value, as well as the mechanic value per hectare, the presence of higher quality of gross marketable output, the presence of short-chain sales, and the hours of labor per hectare. Conversely, the localization in the mountain, the hours of labor, the circulating agricultural capital per hectare, the productivity of labor, and the availability of family labor decrease the farms' propensity to become organic (Table 6).

Table 6. Estimates on probability to adopt organic certification.

	Coeff.	Std. Err.	*p*-Value
Altimetry classification	−0.285	0.132	0.030**
Gender	0.029	0.180	0.873
Young	0.053	0.229	0.817
Added_value	0.908	0.288	0.002***
Mec_value	0.157	0.091	0.082*
GMO_quality	0.868	0.377	0.022**
UAA	0.244	0.370	0.509
Short_sc	0.497	0.284	0.081*
Hours of labour	−1.667	0.445	0.000***
Capes_UAA	−0.006	0.002	0.007***
Land_prod	0.000	0.000	0.566
Lav_prod	−0.052	0.020	0.008***
Activity	0.003	0.001	0.019**
Labf	−7.951	2.890	0.006***
Mecc_UAA	0.005	0.002	0.012**
Mecc_UAA_square	0.000	0.000	0.001***
Geo_1	21.302	163.181	0.896
Geo_3	20.976	163.181	0.898
Cons	−18.626	163.208	0.909

Obs. = 355; pseudo R^2 = 0.16; * *p*-value < 0.1; ** *p*-value < 0.05; *** *p*-value < 0.001.

Table 7 shows the estimates for the average treatment effect on the treated (ATT) based on the stratification matching and the nearest neighbor, respectively. The ATT estimates show a positive effect of the organic certification on the farm TE of +0.06 with the stratification method and +0.08 with the nearest neighbor method, representing in percentage terms an increment in efficiency of around 10%.

Table 7. Organic certification average treatment effect on the treated (ATT) (stratification and nearest neighbor matching (NNM)).

Method	Number of Treated	Number of Control	ATT	Std.Err.	t
Strat. M	103	189	0.060	0.018	3.378
NNM	103	65	0.076	0.028	2.716

5. Discussion

Our results indicate that organic farming is positively associated with technical efficiency in Italian olive farms. This outcome could be explained by considering that organic products benefit from a higher market price as consumers highly appreciate their quality attributes [51,80]. With an interesting exception [81], several studies have shown that a combination of lower input costs as well as a market premium reflecting the consumers' willingness to pay for healthier and environmentally friendly food [82] make organic farms more profitable than conventional ones [52,53,83].

Our findings also showed that all considered inputs of production, namely the working capital, the land capital, and labor, have a positive and significant effect on the GMO of farms. These findings are consistent with previous studies in which the higher capital endowment, both in terms of machines and financial capital, is a critical tool for enhancing productivity at the farm level [79,84]. Mechanization increases the gross marketable output through the timelessness of agricultural operations [85,86]. Conversely, un-mechanized agriculture reveals a decrease in crop yield [87,88]. Furthermore, the availability of financial capital helps increase the gross marketable output by purchasing inputs of production [89]. As for the labor, our results show a direct relationship with output in terms of GMO. Harvesting olives by hand guarantees the best quality of olives, creating a better quality of the final product [90] with a higher price of extra-virgin olive oil, which increases the gross marketable output of the farm.

The negative effect of organic certification on technical inefficiency reveals a positive association of organic certification with TE. This finding is in agreement with previous studies [19,91] showing that organic certification improves farm economic performance by increasing the yield or the price of the final product. At the same time, the result is opposed to that reported by Beuchelt and Zeller [25], who highlighted organic coffee producers as poorer than conventional ones. Farm localization, in terms of altimetry and geographic area, has a significant effect on farm inefficiency. More specifically, if the farm is located in a plain or a hilly area, the inefficiency decreases, while it increases if the farm is located in the central regions [10,92]. Conversely to Julie and colleagues [93], according to whom there are no differences in terms of technical efficiency between diversified and specialized farms, our results are in agreement with Lakner and colleagues [43], showing that diversification decreases technical efficiency in organic farms. This probably occurs because diversified activities could be not adequately remunerated.

The higher impact of organic certification on TE is observed in smaller farms. This is probably owing to the marketing strategy used by small farms [94]. Several authors found that organic producers use direct marketing channels more than conventional producers, thus enabling the producer to gain a premium price for the product [95–98]. In line with what has just been said, we found that the determinants of conversion from conventional to organic olive farms are the production and direct sales of a higher quality of GMO. Indeed, consumers think that organic product is a "premium product", healthy, and environmentally friendly [80]. Moreover, farm labor intensity has a positive impact on the propensity to become organic. In other words, our results have shown that farms with a high ratio between hours of labor and UAA and with a high level of mechanization are more prone to adopt organic certification. These findings are in line with those of Ferjani and colleagues [99], according to whom farmers are skeptical about conversion when they perceive organic farming needs extra work.

Our findings showed the main barriers of conversion from conventional to organic olive farms, such as the following: (i) the localization in the mountain, (ii) the hours of labor, (iii) the circulating agricultural capital per hectare, (iv) the productivity of labor, and (v) the availability of family labor. The cultivation in a mountain area may discourage the organic farming system adoption because pest and disease diffusion, as well as weed infestation, are more difficult to control without the use of pesticides [7,99]. The altimetry may also be a barrier to conversion if the farm is too far from the urban area and its customers, thus not allowing for direct sales [100]. The endowment of financial capital per hectare discourages farm conversion, probably because the availability of circulating agricultural capital helps purchase chemical inputs of production [89], such as fertilizers and pesticides, allowed in conventional agriculture. The productivity of labor reduces the propensity to become organic as the higher crop yield obtained in the conventional system [101,102] increases farm output and, accordingly, labor productivity. As for the availability of family labor, our result is different from those of several previous researchers [103,104], where organic farming is associated with claims of high labor requirements compared with conventional farms. However, a small part of the scientific literature suggests that labor use depends on farm type and farm size [27,104]. In particular, following our finding, Tzouvelekas and colleagues [27] show a lower use of labor in Greek organic olive farms, owing to less labor required for harvesting the lower level of olive yield [27]. Accordingly, a farmer with a high endowment of family labor is more reluctant to adopt organic certification.

6. Conclusions

In recent years, the scientific community and policymakers have agreed about new challenges of agriculture, such as the production of healthy food, adaptation to climate change, protection of natural resources, and landscape conservation. However, despite a growing public awareness of the environmental and social importance of AFSs, the adoption of cleaner agricultural practices (i.e., organic agriculture) is still scarce, even in developed countries such as Italy.

The present paper aimed to identify potential barriers associated with organic certification adoption, analyzing the impact of the organic certification on the economic performances of Italian olive farms, considering technical efficiency in particular. To this end, we developed a stochastic frontier analysis assuming that environmental factors are positively associated with the distance of each farm to the best practice function. The statistical model considers the gross marketable output as the dependent variable, while the working capital together with land capital and labor are the independent variables. Furthermore, we included in the model specific environmental variables to assess the technical inefficiency term. To quantify the effect of organic certification on TE without sample selection bias or endogeneity problems, we designed a quasi-experimental study, implementing a propensity score matching for making a comparison between organic and conventional farms.

The findings showed that organic certification is positively and significantly associated with a higher level of technical efficiency in Italian olive farms (around 10%). Accordingly, it is critical to stimulate the adoption of organic certification in Italian olive farms as it is a win–win alternative to the conventional system, both in economic and environmental terms. The adoption of organic certification could enhance the competitiveness of small and medium Italian farms, thus improving rural development.

Some limitations of the research concern the use of cross-sectional data; although the sample was representative of the Italian olive farms, the cross-sectional design may to a certain extent limit an exact identification of the organic certification effect. Moreover, our estimates could benefit from the inclusion of more variables about the agricultural vocation of the territory. Finally, our estimates do not consider possible sample selection bias on the production function estimates. Thus, further studies may investigate the effect of organic certification on different products and countries and on the economic performances over time, using a panel dataset and trying to analyze different agro-food products.

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