Kashiwagi and Kamiyama
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Effect of adoption of organic farming on technical efficiency of olive-growing farms: empirical evidence from West Bank of Palestine

Kenichi Kashiwagi[1*] and Hajime Kamiyama[2]

*Correspondence: kashiwagi.kenichi.fn@u.tsukuba.ac.jp

[1] Institute of Humanities and Social Sciences, Alliance for Research on the Mediterranean and North Africa, University of Tsukuba, 1-1-1 Tennodai, Tsukuba, Ibaraki 305-8572, Japan
[2] Faculty of Economics, Kushiro Public University of Economics, 4-1-1 Ashino, Kushiro, Hokkaido 085-8585, Japan

Abstract

Organic farming is one of the methods that increases the value added of agricultural products in a sustainable way. This paper examines how the adoption of organic farming has impacted the technical efficiency of Palestinian olive-growing farms in the West Bank. Using cross-sectional data of olive farms in the Jenin governorate, we employ an input-oriented data envelopment analysis framework to compute radial and input use efficiencies. Considering heterogeneity in technology between organic and conventional farming, a metafrontier with a directional distance function approach was applied. As self-selection bias may exist due to the decision to adopt organic farming, we apply the endogenous switching regression method to reduce bias caused by unobserved heterogeneity. Results suggest that organic farms in Jenin are not less efficient than conventional farms. Their organic farming method improves input use efficiency with respect to labor and cost relative to conventional farming. While organic farming is commonly considered to be less efficient and more costly, our findings from Jenin imply that it is, in fact, a more efficient method. We suggest that promoting organic olive farming could offer an effective strategy for small farms to add value, despite the severe geopolitical constraints of farming in the West Bank.

Keywords: Organic farming, Metafrontier, data envelopment analysis, Endogenous switching regression, Olive-growing farms, West Bank

JEL Classification: O12, O13, Q13

Introduction

According to a recent report from World Organic Agriculture, organic olive production has been rapidly expanding across permanent croplands. Over the past 10 years, the area used for organic olive farming has more than doubled. Currently, approximately 20% of the world's organic agricultural land is used for olive cultivation (Willer and Lernoud 2019). Olive cultivation is a major farming activity in the Mediterranean region, in which organic producers develop food and cosmetic products that are labeled with organic certification. The production of organic olives in this region has become increasingly significant, presenting a promising alternative for advancing agriculture (Tzouvelekas et al. 2001a).

In the Mediterranean region, the diffusion of organic olive farming in Palestine has lagged behind, although olive cultivation is a major agricultural activity. The Palestinian Authority, in collaboration with international organizations and nongovernmental organizations (NGOs), has been promoting organic agriculture, yet the distribution of organic areas remained at 7.5% in 2017, less than other that of Mediterranean producers such as France, Spain, Tunisia, and Turkey (Willer and Lernoud 2019). Severe geopolitical constraints under Israeli occupation, including a lack of market access and deterred diffusion of knowledge on organic farming, might have hindered its potential; however, other Mediterranean countries' experiences imply that the diffusion of organic farming and development of organic certified products could offer an effective strategy, even in the occupied territories.

Despite widespread interest in organic production and its significance, some studies have found organic farming methods to be characterized by lower yields and profits, higher fixed costs, and production inefficiencies (Kumbhakar et al. 1991; Cobb et al. 1999; Tzouvelekas et al. 2001a, b; Mayen et al. 2009; Oelofse et al. 2010; de Ponti et al. 2012). Several factors, including compliance with food safety regulations and stringent standards, may impose additional costs. In addition, higher labor costs are detrimental to organic production. In contrast, other studies have suggested that organic methods have a positive impact on the technical efficiency of olive farming. Tzouvelekas et al. (2001a) discovered organic olive-growing farms in Greece to exhibit a higher degree of technical efficiency and lower costs than conventional farms. Galluzzo (2014) suggested that organic olive farms in Italy were more efficient and productive than conventional farms. Artukoglu et al. (2010) asserted that the yields and technical efficiency of organic olive farms exceeded those of conventional farms in Turkey. Regarding profits, Berg et al. (2018) found that organic olive farming in Greece was more profitable than conventional farming, primarily because of the higher market price of organic olive oil. While olive yields from organic and conventional farms do not significantly differ, organic olive farming may still promote higher efficiency.

Several studies of the Mediterranean region reported on the higher productivity and efficiency of organic olive farming; however, they fail to consider the potential endogeneity bias due to self-selection in adopting the organic method. As the observed and unobserved heterogeneity of farms' characteristics may affect the decision to adopt the organic farming method, the distribution of organic and conventional farms is not randomly assigned. Therefore, measured productivity and efficiency may be influenced by self-selection bias due to unobservables. In their analyses of dairy farms, Kumbhakar et al. (1991) and Sipilainen et al. (2005) addressed endogenous self-selection bias in organic farming, and Mayen et al. (2009) employed propensity score matching (PSM) to create quasi-experimental conditions for comparing organic and conventional dairy farms. Kumbhakar et al. (1991) developed an identification framework for the joint estimation of the technical efficiency of dairy farms in Finland and their endogenous selection of technological methods, either conventional or organic. The maximum likelihood method is used to estimate the parameters of production technologies, which are then used to estimate the efficiency of each organic and conventional farm. The authors found that conventional farms are, on average, more technically efficient than organic farms. Mayen et al. (2009) employed PSM to address self-selection into organic farming to compare the productivity and technical efficiency of organic and conventional dairy farms in the US. The authors found heterogeneous technology use among organic and conventional dairy farms in the US and that organic dairy technology is less productive but there is little difference in technical efficiency between the two types of farms. While some studies have addressed the selection bias problem, few relevant studies focus on the case of olive farming.

Given the above, the objective of this study is to examine the effect of the adoption of organic farming on the technical efficiency (TE) of olive-growing farms. Using cross-sectional data of olive farm households collected from the Jenin Governorate of West Bank, we employ input-oriented data envelopment analysis (DEA) to compute TE. We employ the endogenous switching regression (ESR) method to reduce selection bias by controlling for both observed and unobserved heterogeneity (Shiferaw et al. 2014; Wossen et al. 2017). The aforementioned studies on olive production found organic farming to have a positive impact on productivity and efficiency (Tzouvelekas et al. 2001a; Artukoglu et al. 2010; Galluzzo 2014); however, the potential for endogeneity bias may remain due to the self-selection of adopting organic farming. This paper endeavors to fill this gap.

We compute TE using the DEA approach wherein the efficiency scores of individual farms are measured based on the distance from the use of the identical production technology. We compare the TE of organic and conventional farms, assuming that all farms are operating under the same production frontier; however, comparisons of TE scores across farms are only meaningful if the production frontiers of these two groups are identical. If organic farms are operating under different production frontiers than conventional farms, TE scores are not directly comparable. To address this issue, we employ a metafrontier framework with directional distance functions proposed by Färe and Grosskopf (2000) and O'Donnell et al. (2008). In this framework, TE is evaluated relative to a shared metafrontier, which is defined as the boundary of an unrestricted technological set, whereas group-frontiers are defined as boundaries of restricted sets of technology. Hence, we apply a metafrontier DEA approach to compute the TE of organic, conventional farms with respect to global technology and group-specific technology.

Most efficiency studies using the DEA approach have assumed the adoption of common production technologies in the operations of olive-growing farms (Amores and Contreras 2009; Artukoglu et al. 2010; Fousekis et al. 2014; Berg et al. 2018; Niavis et al. 2018). In contrast, we found several studies that assume the presence of different production technologies by using the directional distance functions approach. Beltrán-Esteve (2013) applied an input-oriented directional metadistance function to olive farms in Spain to evaluate the overall and input-specific efficiency of traditional rain-fed mountain and plain olive groves. Investigating olive oil manufacturers in Turkey, Ozden and Dios-Palmores (2016) employed a metafrontier approach to compare TE across different ownership structures. Regarding the production technology of organic and conventional olive farming, Tzouvelekas et al. (2001a) stressed in their analysis of Greek olive farms that organic olive farms face a different production frontier from that of conventional farms, while authors assumed that olive farms operate in the same production frontier. In Palestine, organic farms not only have more access to knowledge related to organic farming including knowledge on soil preparation and compost making, but also develop sales and marketing channels including exports. For the diffusion of organic farming, the Cannan Fair Trade Organization actively extends services to local farms and tries to develop a direct link between individual farms and global consumers. Due to advantages of access to various agricultural information, it is rational to assume that production technology is heterogeneous between organic and conventional farms. Previous studies have not considered the heterogeneity of production technologies of olive growers. For instance, Kashiwagi (2017) estimated a stochastic production frontier of olive-growing farms in Jenin to compare the TE of irrigated and nonirrigated farms, and Kashiwagi (2020) investigated the impact of joining agricultural cooperatives on their productivity and efficiency; however, a nonparametric approach was not employed, nor was the impact of organic farming examined. These studies did not employ a directional metadistance function approach. To our knowledge, few studies have examined the impact of organic farming on the TE of olive-growing farms using a metafrontier framework. Bertran-Esteve and Reig-Martinez (2014) employed metafrontier approach to compare the efficiency of conventional and organic methods for citrus production. The authors found that the distance between the level of efficiency on each group-specific frontier and metafrontier is wider in organic than conventional citriculture. Using metafrontier approach, Aravindakshan et al. (2018) found that the adoption of conservation over traditional tillage affected the technical efficiency of wheat production in South Asia. While these studies applied the metafrontier approach, they do not focus on olive cultivation. For the application to olive-growing farms, Bertran (2013) used metafrontier approach. They found an advantage of the plain olive grove system over the rain-fed mountain olive grove system, but this study did not compare organic and conventional olive farming.

In the present study, we assume that adopting organic farming has a positive impact on the TE of olive production. Our hypothesis also asserts that organic olive farming is more efficient with respect to labor and other inputs than conventional farming. It is not only for olive but also for other agricultural products that organic farming method is generally regarded as technically inefficient and require more cost. Our empirical analysis shed light on this issue, using olive production as example. From a policy perspective, we emphasize the significance of adopting organic farming. The Ministry of Agriculture (MOA), State of Palestine formulated a "National Strategy for Olive and Olive Oil Subsector" in 2014 under the National Agricultural Sector Strategy "Resilience and Development" of 2014–2016. Under this strategy, eight specific objectives were addressed, including improving production and productivity per unit of land, water, labor, and investment; reducing production costs; developing farmers' associations and cooperatives; improving labeling and branding; and making the best use of profitable niche markets, such as organic and Fair Trade markets (MOA 2014a). Organic agriculture is considered a targeted means to increase value added and explore new markets (MOA 2014b). In view of the strategic importance of the olive sector for Palestinian agricultural development, we emphasize the promotion of organic olive production as a promising direction, despite the region's severe geopolitical constraints. In addition, empirical evidence from Jenin of the West Bank that supports efficiency of organic olive farms may have relevant implications that the promotion of organic farming is effective strategy to improve olive productivity throughout the Mediterranean region.

The remainder of this paper is organized in the following manner. Section 2 presents the data collection method used. We explain the models used as an identification strategy in Sect. 3. Section 4 presents the empirical results, which are followed by a discussion in Sect. 5. Section 6 summarizes our conclusions.

Agriculture and olive farming in the West Bank under occupation

Agricultural operations and management in Palestine are constrained not only by climatic conditions but also by geographical and political factors under Israeli occupation. First, the West Bank in Palestine itself has a small area where agricultural land is about 1,105 square kilometers. As most agricultural land locates in mountainous area, the opportunity of land expansion is limited. Second, the West Bank locates mostly in the Mediterranean climate zone with annual precipitation between 300 and 500 mm. Compared to Egypt, Jordan and Israel, annual rainfall in the mountainous area of West Bank is more but water resources are extremely scarce for the Palestinian side due to the limitation of use of groundwater. The Israeli civil administration which governs the occupied territories rarely approves the application of drilling new well proposed by Palestinian Authority. While it is allowed to rehabilitate existing wells and to construct water harvesting facilities and cisterns for collecting rainfall, the development of new well is severely restricted. Third, the West Bank is divided into Area A under the Palestinian National Authority (PNA), Area B which is semi-autonomous area administered by the PNA and Israel, and Area C which is fully administrated by Israel. In Area C that makes up over 60% of the West Bank, Jewish settlement has been constructed, which results in the isolation of Palestinian land in the occupied territories. Moreover, the Israeli government started building a separation barrier (separation wall) along the Green Line and inside parts of the West Bank. Due to the growing Jewish settlement and extension of the separation wall, movement of Palestinian people, their access to agricultural inputs and markets are severely constrained.

Under such geographical and political situation, it is difficult to expand land, develop new water resources, and procure agricultural inputs including fertilizers and modern varieties. In addition, the Israeli civil administration imposes restrictions on import of dual use goods including chemical fertilizers which are used for civilian purposes. These constraints severely hinder the possibility of development of agriculture in the West Bank, where most smallholders suffer from unstable production and uncertainties, limited access to modern inputs, finance and export markets. Nevertheless, the development of organic farming is considered as one of the effective directions for agricultural development. The role of organic farming becomes extremely important for adding value to the current production and for expanding access to international markets. The dual use restriction on chemical fertilizers has been conversely promoting adoption of organic farming. Within agricultural sector, cultivation of olives and olive oil extraction have a strategic position and have a significant relevance in production, job creation and export. Olive production comprises about 3.5% of agriculture production value (MOA, 2014b). They identified olive cultivation and olive oil production as one of the main subsectors for agriculture development. While olive harvest is highly volatile, olive oil has a significant export potential among tradable goods in Palestine (UNCTAD, 2011).

Currently, the MOA designed "National Strategy for Olive and Olive Oil Subsector in Palestine" and "Olive Oil Sector Export Strategy 2014–2018" to identify the specific role of olive and olive oil sector. In these sectoral development strategies, the role of organic olive farming was addressed to improve productivity, competitiveness, and efficiency in the olive oil value chain. In the sectoral export strategy, exploitation of marketing advantages of Palestinian olive oil including high quality, natural organic production and fair trade is regarded as important vision to realize its export potential (MOA 2014b).

Despite the strategic importance of olive production and organic farming in particular, the current level of production remained low in comparison with the nearly identical climatic conditions such as Israel and Jordan. The average land productivity in Israel was from 1.5 to 2.5 tons per hectare, while it ranged from 0.4 to 2.4 tons in Palestinian (UNCTAD 2015). Jordanian olive farming realized about 16.9% higher yield than that of Palestine (MOA 2014b). According to the MOA, the land productivity lagged behind compared with their potential but it is possible to improve by 30–40% as far as farmers adopt the appropriate technologies (MOA 2014b). Production cost of olive farming in the West Bank is roughly 30% higher than those in Jordan (World Bank 2006). This low productivity and higher cost imply inefficiencies exists in olive production. The distance between current output and the maximum possible output with available inputs and given technology is huge. Hence, it is meaningful to quantify how organic farming affects technical efficiency and whether olive farmers are efficient in terms of labor and other inputs. To this end, we employ the input-oriented efficiency evaluation to measure the level of efficiency of both organic and conventional farms, and to estimate the impact of the adoption of organic farming. Reduction of inputs while maintaining a current output is crucial to improve efficiency under severe constraints. We emphasize organic farming is one of the promising directions under Israeli occupation. To quantify the magnitude of impact of the adoption of organic farming on technical efficiency provides empirical evidence that support the national olive oil strategy.

Data

We implemented a survey entitled, "Survey of Olive Farms in the West Bank, Jenin," in September 2015 and September 2016 in collaboration with the Palestinian Central Bureau of Statistics. The survey period occurred during the harvest season when olive farms are actively operating. We collected household data on olive-growing farms. The Jenin governorate, located in the northern part of the West Bank, is one of the most active olive oil producing areas among the Palestinian governorates.[1] We also chose Jenin because it is one of the governorates in which organic farming is popular. Cooperatives and NGOs, including the Canaan Fair Trade organization, actively promote the production and marketing of organic olive oil.[2] Based on the Agricultural Census of 2010 implemented by PCBS, we selected the number of sample farms depending on the geographical distribution of olive farms by locality. We collected household data of olive-growing farms, which were distributed by a strata design. We employed one-stage

[1] According to the Olive Presses Survey 2019 of the Palestinian Central Bureau of Statistics, Ministry of Agriculture, the number of operating olive presses is the highest in Jenin and Tubas. The number of operating olive presses in Jenin were 61, 59 in 2015, 2016, respectively.

[2] Cannan Fair Trade; see https://canaanpalestine.com/ (accessed: February 28, 2021).

stratified random sampling, with a response rate of 89.5%. For DEA analysis, we used a sample of 261 farms with nonnegative production inputs, 80 (30.7%) of which adopted organic farming, and 181 of which were conventional farms (69.3%) that did not adopt organic farming. The oldest organic olive farm in the sample had been operating since 2006, and the organic olive farms were operating for an average of 7 years. While we did not use survey weight for the estimations, the number of sample farms reflected the geographical distribution of olive farms by locality.

Table 1 presents descriptions and summary statistics for the variables used. The variable of production value per land is measured as value of olive production divided by cultivated land area, which is used as an output for DEA analysis. The number of family and wage labor, the number of olive trees, and total cost are used as input variables. These three inputs are measured by per unit of land. We present the difference in mean values between organic and conventional farms in Table 2. Production per land which represents land productivity does not differ statistically between organic and conventional farms. In contrast, inputs of labor, costs, and tree plantation are more intensive for conventional farms. Paid cost per land of organic farms is significantly lower than that of conventional farms, while the difference in paid wage cost is insignificant between the two groups. In the West Bank, organic farming applies compost without using chemical fertilizer and pesticides purchased from local market, which results in their lower cost relative to conventional farms. These input–output figures imply that organic farms produce a similar level of output with fewer inputs compared to conventional farms. Regarding control variables, the mean differences are statistically significant for farm years of operation and the number of olive trees. On average, organic farms have more experience in farming than conventional farms. Surprisingly, the number of trees tends to be higher for organic farms than for conventional farms, while organic farms have lower density of trees as measured by the number of trees per unit of land. This implies that organic farms are larger than conventional farms. The mean difference in the price of olive oil is statistically significant. The price of oil extracted using olives from organic farms is higher than that from conventional farms. It is notable that 68.6% of organic farms have access to Canaan Fair Trade, whereas only 3.3% of conventional farms have access. This implies that Canaan is an active promoter of the diffusion of organic farming. Thus far, we have observed the mean differences between organic and conventional farms; however, we are unable to make any inferences regarding the impact of organic farming without controlling for other potentially confounding factors.

Model

Directional distance function and data envelopment analysis (DEA)

We employ the directional distance function methodology developed by Färe and Grosskopf (2000) and O'Donnell et al. (2008). Using DEA, Sáez-Fernández et al. (2012), Beltrán-Esteve (2013), and Beltrán-Esteve and Reig-Martínez (2014) applied a directional distance function approach to assess both TE and input use efficiency. Following Niavis et al. (2018) and Stillitano et al. (2019), who applied an input-oriented DEA approach to olive-growing farms, we set the decision-making unit (DMU) as an individual olive-growing farm that tries to use production factors to minimize farm inputs. This input-oriented DEA model measures efficiency scores based on how possible it is

Table 1 Description and summary statistics of variables. *Source*: Authors' calculation based on survey data

Variables	Description	Mean
Production value per land	Production value of olives per unit of land (hundred NIS/ha)	64.312
		(44.645)
Labor inputs per land	Total number of family and wage labor used for olive cultivation per unit of land (number/ha)	7.319
		(8.075)
Paid cost per land	Total paid cost including fertilizer, pesticides, water and others per unit of land (hundred NIS/ha)	10.169
		(15.710)
Paid wage cost per land	Total paid wage cost per unit of land (hundred NIS/ha)	19.261
		(24.345)
Trees per land	Total number of olive trees per unit of land (hundred/ha)	1.529
		(0.417)
Organic farming	1 if farm adopted organic farming, 0 otherwise	0.307
		(0.462)
Family labor	Number of family labor used for olive cultivation (number)	4.636
		(4.138)
Wage labor	Number of wage labor used for olive cultivation (number)	4.153
		(6.189)
Capital-land ratio	Ratio of capital to land area (hundred NIS/ha)	25.379
		(120.457)
Age	Age of household head (years)	54.739
		(11.456)
Education	Years of education of household head (years)	12.513
		(4.716)
Farm years	Years of farming (years)	22.211
		(12.309)
Olive trees	Total number of olive trees (hundred)	4.104
		(4.309)
Age olive trees	Average age of olive trees (years)	38.824
		(23.341)
Share of irrigated area	Share of irrigated area (%)	10.010
		(18.829)
Price olive oil	Price of olive oil (NIS/kg)	22.789
		(2.319)
Biennial bearing	1 if fam had a good harvest year due to biennial bearing, 0 otherwise	0.479
		(0.501)
Distance to mill	Distance to the nearest olive oil mill (km)	4.200
		(4.912)
Access to Cannan	1 if farmer have access to Cannan fair trade, 0 otherwise	0.234
		(0.424)
Modern olive presses	Number of operating modern and full automatic olive presses in Jenin (number)	58.483
		(2.961)

NIS indicates new Israeli shekel. Standard deviations are in parentheses

for each DMU to reduce inputs compared to the best performers. We apply an input-oriented approach for the computation of TE and input use efficiency with respect to the metafrontier and group-specific frontiers.

Table 2 Summary statistics and mean differences between organic and conventional farms. *Source*: Authors' calculation based on survey data

	Organic farms (n = 80)	**Conventional farms (n = 181)**	
Variables	Mean	Mean	Mean difference
Production value per land	67.470	62.916	4.554
	(41.370)	(46.060)	
Labor inputs per land	3.387	9.057	− 5.670***
	(3.395)	(8.901)	
Paid cost per land	5.348	12.300	− 6.952***
	(8.772)	(17.545)	
Paid wage cost per land	20.981	18.500	2.481
	(28.388)	(22.372)	
Trees per land	143.585	157.020	− 13.435**
	(41.523)	(41.178)	
Family labor	4.875	4.530	0.345
	(4.126)	(4.151)	
Wage labor	3.950	4.243	− 0.293
	(4.449)	(6.828)	
Capital-land ratio	18.490	28.423	− 9.933
	(31.441)	(143.158)	
Age	55.738	54.298	1.439
	(12.377)	(11.032)	
Education	12.725	12.420	0.305
	(4.715)	(4.727)	
Farm years	24.725	21.099	3.626**
	(11.085)	(12.683)	
Olive trees	6.027	3.255	2.772***
	(4.969)	(3.689)	
Age olive trees	37.988	39.193	− 1.206
	(21.509)	(24.155)	
Share of irrigated area	7.639	11.057	− 3.419
	(13.671)	(20.651)	
Price olive oil	23.419	22.510	0.909***
	(1.818)	(2.462)	
Biennial bearing	0.525	0.459	0.066
	(0.503)	(0.500)	
Distance to mill	4.320	4.148	0.172
	(6.135)	(4.280)	
Access to Cannan	0.688	0.033	0.654***
	(0.466)	(0.180)	
Modern olive presses	58.700	58.387	0.313
	(3.004)	(2.945)	

*, **, *** indicate significant at the 10%, 5%, 1% level, respectively. Standard deviations are in parentheses

Following Färe and Grosskopf (2000) and O'Donell et al. (2008), the metatechnology set denoted by T denotes all feasible combinations of inputs and output with the present level of technology and is defined as $T = \left[\left(\boldsymbol{x}, y\right) : \boldsymbol{x} \geq 0; y \geq 0; \boldsymbol{x} \text{ can produce } y\right]$, where y denotes a single output and $\boldsymbol{x}$ is a nonnegative vector of inputs. T is assumed to satisfy the standard properties, including a convex, closed set, and inputs and outputs are freely disposable (Färe and Grosskopf 2000). While O'Donnell et al. (2008) proposed a metafrontier framework using an output-oriented distance function, we employ an input-oriented distance function. We assess the maximum feasible proportional savings of all inputs while maintaining the current level of output. Following Sáez-Fernández et al. (2012), the directional metadistance function is defined by the following:

$$\overrightarrow{MD}[\boldsymbol{x}, y; \boldsymbol{g} = (-\boldsymbol{x}, \boldsymbol{0})] = \mathrm{Sup}\left[\theta | \left((1-\theta)\boldsymbol{x}, y\right) \in T\right], \tag{1}$$

where $\boldsymbol{g} = (-\boldsymbol{x}, \boldsymbol{0})$ is a direction vector and θ represents the distance of a pair $(\boldsymbol{x}, y)$ to the metafrontier. This directional metadistance function obtains the maximum level of inputs that each DMU can radially reduce while maintaining the current level of output. In this equation, TE is measured by $(1-\theta)$.

We consider the case in which the DMUs in our sample are divided into h groups. DMUs in each group are prevented by resource, regulatory, and other environmental constraints from choosing the combinations of inputs and output in the metatechnology set (O'Donnell et al. 2008; Sáez-Fernández et al. 2012). This assumption infers that the group-specific technology set, T^h, contains the combinations of inputs and output available to the farms in the hth group. Hence, the group h specific technology set is given by $T^h = \left[(\boldsymbol{x}, y) : \boldsymbol{x} \geq 0; y \geq 0;\ \boldsymbol{x} \text{ can be used by farms in group } h \text{ to produce } y\right]$. Based on this group-specific technology, the directional distance function that measures efficiency with respect to T^h can be represented by the following:

$$\vec{D}^h[\boldsymbol{x}, y; \boldsymbol{g} = (-\boldsymbol{x}, \boldsymbol{0})] = \mathrm{Sup}\left[\theta^h | \left(\left(1-\theta^h\right)\boldsymbol{x}, y\right) \in T^h\right], \tag{2}$$

where θ^h captures the distance of a pair $(\boldsymbol{x}, y)$ to the group h frontier. This directional distance function captures the maximum attainable proportional reduction of inputs for technology group h. The group-specific directional distance function equals or is below the directional metadistance function, i.e., the metafrontier envelopes group h frontiers (O'Donnell et al. 2008; Sáez-Fernández et al. 2012; Beltrán-Esteve 2013).

As metatechnology envelops group technologies, we can observe the distance between group h frontiers and the metafrontier. This gap in technology of a group h is measured as the metatechnology ratio by the difference the between level of efficiency that can be achieved within the hth group-specific restrictions and the best performance achieved without such restrictions. Following Sáez-Fernández et al. (2012), we define the metaefficiency of TE of $(\boldsymbol{x}, y)$ as the distance from metatechnology:

$$\text{Metaefficiency} = 1 - \overrightarrow{MD}[\boldsymbol{x}, y; \boldsymbol{g} = (-\boldsymbol{x}, \boldsymbol{0})] = 1 - \theta. \tag{3}$$

An observed pair $(\boldsymbol{x}, y)$ is fully efficient, as evaluated by the metafrontier, if and only if, $\theta = 0$. Similarly, TE with respect to the group h is given by the following:

$$\text{Efficiency}^h = 1 - \vec{D}^h[\boldsymbol{x}, y; \boldsymbol{g} = (-\boldsymbol{x}, \boldsymbol{0})] = 1 - \theta^h. \tag{4}$$

Following O'Donnell et al. (2008), and Sáez-Fernández et al., (2012), the input-oriented metatechnology ratio (MTR) for group h farms in a direction that proportionally reduces all inputs can be defined as:

$$\text{Metatechnology Ratio}^{h}[\boldsymbol{x}, y; \boldsymbol{g} = (-\boldsymbol{x}, \boldsymbol{0})] = \frac{\text{Metaefficicency}}{\text{Efficiency}^{k}} = \frac{1-\theta}{1-\theta^{h}}. \tag{5}$$

The upper bound of both metaefficiency and efficiency is one, which is fully technically efficient. The MTR measures the technological gap between the technology of group *h* and the metatechnology. The value assesses the distance from the group *h* specific frontier to the unrestricted metafrontier in a direction whereby all inputs can be radially reduced without reducing the output level (Sáez-Fernández et al. 2012; Beltrán-Esteve 2013).

For empirical application, we compute directional distance functions using DEA techniques. The DEA method is a nonparametric approach that involves a mathematical linear programming technique (Farrell 1957; Charnes et al. 1978; Cooper et al. 2007). We employ an input-oriented DEA model for the estimation of metafrontier and group-specific frontiers, assuming variable returns to scale (VRS) (Banker et al. 1984).We set that a set of $k=1, \ldots, K$ DMUs exist that are using a set of M inputs, represented by $x^{k}{}_{m}$, to produce y output, represented by y^{k}. Based on the DEA framework, the optimization program that calculates distance from the metafrontier for DMU k' in Eq. (1) is:

$$\begin{aligned}
&\underset{\theta_{all}^{k'}, z^{k}}{\text{maxmize}}\, \theta_{all}^{k'},\ k\prime \in k = 1, \ldots, K \\
&\text{s.t.} - y^{k'} + \sum_{k=1}^{K} \omega^{k} y^{k} \geq 0, \\
&\left(1 - \theta_{\text{all}}^{k'}\right) x_{m}^{k'} - \sum_{k=1}^{K} \omega^{k} x_{m}^{k} \geq 0,\ m = 1, \ldots, M \\
&\sum_{k=1}^{K} \omega^{k} = 1, \\
&\omega^{k} \geq 0,
\end{aligned} \tag{6}$$

where ω^{k} is a restriction that implies the sum of ω^{k} equal to one allows for a VRS technology. The value of by $\theta_{\text{all}}^{k\prime}$ captures the distance of the farm k' from the metafrontier, which is generated by solving the linear programming problem of Eq. (6) K times. $\theta_{\text{all}}^{k'}$ captures the maximum level of all inputs that the farm k' can be proportionally reduced while keeping the observed level of output constant.

Equation (6) can be applied to calculate the TE of *j*th input $x^{k'}{}_{j}$ for farm k' wherein only input $x^{k'}{}_{j}$ is reduced. We calculate the input use efficiency score for each DMU by observing the possible reduction in one input without changing all other inputs and output. The *j*th input use efficiency of each farm k' denoted by $\theta_{j}^{k'}$ is computed by the following:

$$
\begin{aligned}
&\underset{\theta_j^{k'}, z^k}{\text{maxmize}}\, \theta_j^{k'}, k\prime \in k = 1, \ldots, K \\
&\text{s.t.} - y^{k'} + \sum_{k=1}^{K} \omega^k y^k \geq 0, \\
&\left(1 - \theta_j^{k'}\right) x_j^{k'} - \sum_{k=1}^{K} \omega^k x_j^k \geq 0, j \in m \text{ and } j \notin -j \\
&x_{-j}^{k'} \geq \sum_{k=1}^{K} \omega^k x_{-j}^k, -j \in m \\
&\sum_{k=1}^{K} \omega^k = 1, \\
&\omega^k \geq 0.
\end{aligned}
\tag{7}
$$

We compute efficiency scores by the directional metadistance function of Eq. (1), but efficiency scores for the group h frontier can be calculated in a similar fashion. Following Eq. (2), the distances to the group h frontier denoted by $\theta_{\text{all}}^{hk\prime}$ are computed using observations of DMU belonging to group h. Similarly, observations within group h elicit the input-specific efficiency of group h ($\theta_j^{hk\prime}$).

Endogenous switching regression (ESR)

We examine the impact of the adoption of organic farming on computed efficiency scores. This is simply given by the ordinary least squares (OLS) regression of TE on a binary variable of the adoption of organic farming with several control variables. However, in the absence of the random assignment of organic farming, this method produces biased coefficients under misspecification due to the limited availability of observable control variables. Even if we apply a matching method to mitigate the selection bias by estimating propensity scores based on observable covariates, unobserved heterogeneity may affect both the choice of farming and the outcome variable. For instance, farmers' motivation and ability to produce value-added products, which are not observable, may influence the adoption of organic farming, but such unobservable characteristics also affect efficiency of production. Farmers with greater motivation and ability to improve productivity are more likely to adopt organic farming, which may result in selection bias and an underestimation of treatment effects. Not considering the endogeneity of the adoption of organic farming would result in biased estimated parameters. To address this endogenous bias caused by omitted variables, we employ ESR to control both observable and unobservable heterogeneous characteristics of farms (Maddala 1983; Di Falco et al. 2011; Shiferaw et al. 2014; Oscar et al. 2015; Ma and Abdulai 2016; Wossen et al. 2017). This method implements the full-information maximum likelihood approach by simultaneously estimating the selection and outcome equations (Maddala and Nelson 1975; Lokshin and Sajaia 2004).

The framework for analyzing the decision to adopt organic farming can be modeled following random utility theory (McFadden 1974). Assume that the ith farmer is facing the decision whether to adopt organic farming. Let U_c represent the benefits associated with conventional farming and let U_o represent the benefits of the adoption of organic farming. A_i^* represents a latent variable which captures the expected benefits from adoption choice of organic farming. The latent variable is not directly observed but can be expressed as follows:

$$A_i^* = \boldsymbol{z_i}\prime\boldsymbol{\gamma} + \mu_i \text{ with } A_i = \begin{cases} 1 & \text{if } A_i^* > 0 \\ 0 & \text{otherwise,} \end{cases} \tag{8}$$

where A_i is an observable binary variable whether ith farm adopted organic farming or not. Individual farm will choose to adopt organic farming ($A_i = 1$), if $A_i^* > 0$, and 0 otherwise. $\boldsymbol{z_i}$ denotes a vector of observed characteristics that affect the expected benefits; $\boldsymbol{\gamma}$ is a vector of parameters to be estimated; and μ_i is the error term. Equation (8) implies that the farmer will adopt organic farming if $A_i^* = U_o - U_c > 0$.

The outcome equations conditional on adoption, can be specified by the following two regime equations for organic and conventional farms:

$$\text{Regime 1}: Y_{oi} = \boldsymbol{H_i}\prime\boldsymbol{\beta_o} + \varepsilon_{oi} \text{ if } A_i = 1, \tag{9a}$$

$$\text{Regime 2}: Y_{ci} = \boldsymbol{H_i}\prime\boldsymbol{\beta_c} + \varepsilon_{ci} \text{ if } A_i = 0, \tag{9b}$$

where Y_{oi} and Y_{ci} are outcome variables for organic and conventional farms, respectively; $\boldsymbol{H_i}$ denotes a vector of exogenous variables; $\boldsymbol{\beta_o}$ and $\boldsymbol{\beta_c}$ are vectors of parameters to be estimated; ε_{oi} and ε_{ci} are the error terms associated with the outcome variables.

Following Maddala (1983) and Lokshin and Sajaja (2004), the error terms in Eqs. (8), (9a), and (9b) are assumed to have a trivariate normal distribution with a zero mean and the covariance matrix is specified as:

$$\text{cov}(\mu, \varepsilon_o, \varepsilon_c) = \begin{bmatrix} \sigma_\mu^2 & \sigma_{o\mu} & \sigma_{c\mu} \\ \sigma_{o\mu} & \sigma_o^2 & . \\ \sigma_{c\mu} & . & \sigma_c^2 \end{bmatrix}, \tag{10}$$

where $\sigma^2_\mu = \text{var}(\mu)$, $\sigma^2_o = \text{var}(\varepsilon_o)$, $\sigma^2_c = \text{var}(\varepsilon_c)$, $\sigma_{o\mu} = \text{cov}(\mu, \varepsilon_o)$, and $\sigma_{c\mu} = \text{cov}(\mu, \varepsilon_c)$. In Eq. (10), the variance of σ^2_μ is assumed to be equal to one, since the coefficients are estimable only up to a scale factor (Maddala 1983). The covariance between ε_o and ε_c is not defined, since Y_{oi} and Y_{ci} are not observed simultaneously. Due to selection bias, the error term of Eq. (8), μ_i, is correlated with the error terms of outcome Eqs. (9a) and (9b) (ε_{oi} and ε_{ci}). Hence, as $\text{corr}(\mu, \varepsilon_o) \neq 0$ and $\text{corr}(\mu, \varepsilon_c) \neq 0$, the expected values of ε_{oi} and ε_{ci} conditional on the sample selection are nonzero:

$$E[\varepsilon_{oi}|A_i = 1] = \sigma_{o\mu}\frac{\varphi(\boldsymbol{z_i}\prime\boldsymbol{\gamma})}{\Phi(\boldsymbol{z_i}\prime\boldsymbol{\gamma})} = \sigma_{o\mu}\lambda_{oi},$$

and

$$E[\varepsilon_{ci}|A_i = 0] = -\sigma_{c\mu}\frac{\varphi(\boldsymbol{z_i}\prime\boldsymbol{\gamma})}{1 - \Phi(\boldsymbol{z_i}\prime\boldsymbol{\gamma})} = \sigma_{c\mu}\lambda_{ci}, \tag{11}$$

where ϕ represents the standard normal probability density function; Φ denotes the standard normal cumulative density function; and λ_{oi} and λ_{ci} are the inverse Mills ratios, where $\lambda_{oi} = \phi(\boldsymbol{z_i}'\boldsymbol{\gamma})/\Phi(\boldsymbol{z_i}'\boldsymbol{\gamma})$ and $\lambda_{ci} = -\phi(\boldsymbol{z_i}'\boldsymbol{\gamma})/[1 - \Phi(\boldsymbol{z_i}'\boldsymbol{\gamma})]$. The decision to adopt organic farming and outcomes are correlated if the estimated covariance, $\sigma_{o\mu}$ and $\sigma_{c\mu}$, are statistically significant. This implies that the null hypothesis of the absence of sample selection bias is rejected.

From the above described ESR model, we can estimate the average treatment effect on treated (ATT) and untreated (ATU) farms by investigating the expected values of outcomes in actual and counterfactual scenarios for both organic and conventional farms (Di Falco et al. 2011; Shiferaw et al. 2014; Wossen et al. 2017).

The conditional outcome expectation for farms adopting organic farming (observed in the sample) is defined as follows:

$$E(Y_{oi}|A_i = 1) = \boldsymbol{H}'_{oi}\boldsymbol{\beta_o} + \sigma_{o\mu}\lambda_{oi}. \tag{12a}$$

For conventional farms (observed in the sample), the conditional expectation of is:

$$E(Y_{ci}|A_i = 0) = \boldsymbol{H}'_{ci}\boldsymbol{\beta_c} + \sigma_{c\mu}\lambda_{ci}. \tag{12b}$$

In contrast, the expected outcome value of the counterfactual hypothetical case for organic farms had they decided not to adopt organic farming is as follows:

$$E(Y_{ci}|A_i = 1) = \boldsymbol{H}'_{oi}\boldsymbol{\beta_c} + \sigma_{c\mu}\lambda_{oi}. \tag{12c}$$

Similarly, as a counterfactual, the value for conventional farms had they decided to adopt organic farming is as follows:

$$E(Y_{oi}|A_i = 0) = \boldsymbol{H}'_{ci}\boldsymbol{\beta_o} + \sigma_{o\mu}\lambda_{ci}. \tag{12d}$$

We can calculate the ATT as the difference between the expected outcome from Eqs. (14a) and (14c):

$$\mathrm{ATT_{ESR}} = E[Y_{oi}|A_i = 1] - E[Y_{ci}|A_i = 1] = H'_{oi}(\beta_o - \beta_c) + \lambda_{oi}\left(\sigma_{o\mu} - \sigma_{c\mu}\right). \tag{13}$$

The first term on the right-hand side of Eq. (13) captures the expected difference in the mean outcome of organic farms, if organic farms exhibited characteristics similar to those of conventional farms. The second term (λ) represents potential effects of difference due to unobservable farms' characteristics.

Likewise, the ATU is derived by taking the difference in the expected outcome between Eqs. (12b) and (12d) as follows:

$$\mathrm{ATU_{ESR}} = E[Y_{oi}|A_i = 0] - E[Y_{ci}|A_i = 0] = H'_{ci}(\beta_o - \beta_c) + \lambda_{ci}\left(\sigma_{o\mu} - \sigma_{c\mu}\right). \tag{14}$$

The first term on the right-hand side of this equation represents the expected difference in the mean outcome of conventional farms, if they exhibited similar characteristics to those of organic farms. The second term (λ) absorbs the potential effects of unobserved characteristics.

For the estimation of ESR model, we need at least one exogenous variable as an instrument within $\boldsymbol{z}_i$ (Adegbola and Gradebroek 2007; Shiferaw et al. 2014). Following Di Falco et al. (2011), Shiferaw et al. (2014), Ma and Abdulai (2016), and Wossen et al., (2017), we used access to the Canaan Fair Trade organization and the number of operating modern olive presses (olive oil processors) as instruments. We presume that the adoption behavior of farms may be affected by access to information on organic farming through the support and services provided by the Canaan Fair Trade organization. Also, the existence and number of processors can be regarded as factors beyond the farms' own decision (Wossen, et al. 2017). The instrument should affect farmers' decision of adopting organic farming but has no direct effect on the technical efficiency of production except through its effect on the farmers' adoption of organic farming. The adoption behavior of farmers can be largely affected by access to certain agricultural information sources (Di Falco et al. 2011; Kabunga et al. 2012; Shiferaw et al. 2014; Oscar et al. 2015). Likewise, distance to certain market also affect incentive for farmers to adopt and the intensity of adoption (Shiferaw et al. 2014; Wossen et al. 2017). We used access to the Canaan Fair Trade organization and the number of operating modern olive presses (olive oil processors) as instruments. It is presumed that the adoption behavior of farms may be affected by access to information on organic farming through the support and services provided by the Canaan Fair Trade organization. Also, the existence and number of processors can be regarded as factors beyond the farms' own decision (Wossen, et al. 2017). We consider that these instruments are likely to be correlated with the adoption of organic method but are unlikely to influence the technical efficiency directly or correlated with unobserved errors in Eq. (9a) and (9b).

Following Di Falco et al. (2011) and Kumar et al. (2018), we applied a falsification test to examine the validity of the two instruments. As demonstrated in Appendix Table 8, coefficients of the instruments in the selection equation adopting organic farming are statistically significant at the 1% level. The Wald test rejects the null hypothesis that estimated parameters jointly equal zero ($\chi^2 = 44.88$, $p = 0.000$). In contrast, estimated coefficients of the two instruments on the outcome equation are insignificant for both organic and conventional farms. An F-test cannot reject the null hypothesis that estimated coefficients of instruments jointly equal zero (i.e., $F = 1.990$, $p = 0.144$ for organic farms, $F = 2.080$, $p = 0.128$ for conventional farms). These results validate the two instruments as strongly correlated with the adoption of organic farming, but not correlate with the outcome variable. In addition, we estimated the ESR using the heteroscedastic instruments proposed by Lewbel (2012, 2018a, 2018b). Following empirical application by Lin et al. (2022), we used additional instrumental variables for the robustness check. The estimated ATT and ATU in Table 9 are stable compared with the ESR using original two instruments, which shows estimated parameters remain robust.

Empirical results

DEA

We used General Algebraic Modeling System (GAMS) software to compute the efficiency scores of the metafrontier and group frontiers. For the specification of the input-oriented DEA model, one output and three input variables were used (labor, paid cost, and trees). Following Beltrán-Esteve (2013), and Beltrán-Esteve and Reig-Martínez (2014), all variables are measured per unit of land; thus, output is measured as olive production in kg per ha, i.e., land productivity. Input variables include the number of laborers per ha, the cost per ha, and the number of trees per ha. We compute specific input use efficiency concerning the three inputs of labor use efficiency, cost use efficiency, and tree use efficiency. For instance, labor use efficiency indicates the possible reduction in

Table 3 Estimation of technical efficiency (TE) for metafrontier and group frontier and metatechnology ratio (MTR). *Source*: Authors' calculation based on survey data

	Mean	Standard deviation	Minimum	Maximum
TE with respect to metafrontier				
Organic farm	0.699	0.205	0.350	1
Conventional farm	0.600	0.170	0.319	1
TE with respect to group frontier				
Organic farm	0.703	0.207	0.350	1
Conventional farm	0.683	0.187	0.320	1
MTR				
Organic farm	0.994	0.021	0.865	1
Conventional farm	0.883	0.097	0.527	1

labor use while holding trees, cost, and output constant. Overall, the mean value of the computed TE of the metafrontier under the VRS assumption is 0.630, ranging from a minimum of 0.318 to a maximum of 1.0. The efficacy score of olive farms in Jenin is generally low compared to those of others in Mediterranean countries. The computed TE of olive farms in Greece by an input-oriented DEA model with a VRS assumption was measured as 0.860, on average (Niavis et al. 2018). Similarly, the estimated mean efficiency score of olive farms in southern Italy, employing input-oriented DEA under a VRS assumption, was measured as 0.823 and 0.835 for intensive and traditional farms, respectively (Stillitano et al. 2019). In Turkey, the efficiency score calculated with a VRS input-oriented DEA was recorded as 0.942 (Artukoglu et al. 2010). While the operational inefficiency of olive farms in Jenin appears to be remarkable, the empirical results suggest that inputs can be reduced by 37.0% to maintain the current level of output. Regarding input use efficiency, the mean labor use efficiency level was 0.234, while it was 0.615 for the input of trees. Cost efficiency was measured as 0.140, being the lowest value of the three inputs examined. Sources of inefficiency may be found in labor use and costs.

The TE scores of the metafrontier, group frontiers, and MTR are presented in Table 3. The mean level of TE of the metafrontier is computed at 0.699 for organic farms, whereas it is 0.600 for conventional farms; thus, the mean of TE is 0.099 higher for organic farms than for conventional farms. The TE of the group frontier presents the operating efficiency of farms within their technological group. The average level of the group-specific TE of organic farms is 0.703. When organic farms are compared to the best practice within their own group in a direction that proportionately reduces all inputs, organic farms could reduce their inputs by 29.7%, on average, while maintaining their current level of output. In contrast, the average TE of conventional farms is 0.683 when comparing farms to the best practice in their own group. With reference to their own technology, efficiency scores are evaluated to be somewhat higher in the group of conventional farms. Although we cannot directly compare group-specific TE between organic and conventional farms, we can assert that organic farms are closer to their own production frontier than conventional farms. Next, the distance between the metafrontier and group-specific frontier is measured by the MTR. A higher MTR indicates how closely farms are operating to the metafrontier. The MTR of organic farms is computed at 0.994, suggesting that organic farms are extremely close to the metafrontier. The maximum

Table 4 Estimation of input use efficiency for metafrontier and group frontier and metatechnology ratio (MTR). *Source*: Authors' calculation based on survey data

	Labor		Paid cost		Tree	
	Mean	**Standard deviation**	**Mean**	**Standard deviation**	**Mean**	**Standard deviation**
Input use efficiency with respect to metafrontier						
Organic farm	0.394	0.330	0.238	0.341	0.671	0.210
Conventional farm	0.163	0.202	0.097	0.193	0.590	0.171
Input use efficiency with respect to group frontier						
Organic farm	0.419	0.333	0.266	0.356	0.675	0.213
Conventional farm	0.279	0.307	0.218	0.323	0.653	0.196
MTR						
Organic farm	0.925	0.115	0.891	0.167	0.995	0.021
Conventional farm	0.658	0.234	0.474	0.201	0.915	0.098

reduction of inputs that organic farms can achieve to maintain current levels of output is approximately 0.06% of the maximum possible input reduction when using the same inputs and given production technology represented by the metafrontier. In contrast, the MTR is evaluated at 0.883 for conventional farms with reference to the metafrontier and their own group frontier. This lower MTR suggests that closeness between the metafrontier and group frontier differs between organic and conventional farms. This MTR indicates that the maximum feasible reduction of inputs to maintain the current production level is 11.7% of the maximum possible input reduction when using the same technology under the metafrontier.

Table 4 presents the input use efficiency scores of the metafrontier, group frontiers, and MTR. The mean value of the TE of organic farms evaluated by the metafrontier is higher than that of conventional farms in terms of labor and costs, whereas tree use efficiency is higher for conventional farms. These results suggest that conventional farms are more inefficient than organic farms with respect to the input of labor and paid costs. On average, conventional farms could reduce labor input by 83.7% to maintain current output levels. Consequently, conventional farmers can reduce current costs by 80.3% on average without changing production levels. In reference to group frontiers, it should be noted that costs may be a source of inefficiency for both groups. On average, organic farms could reduce their current costs by up to 26.6%, whereas conventional farms could do so by up to 21.8%. Conversely, the input of trees is more efficiently used in both farm groups. We cannot directly compare the TE evaluated for each group frontier between the two groups; however, the maximum possible reduction of labor input with respect to each group frontier is greater for conventional farms than organic farms. The MTR results for input use efficiency suggest that organic farms are operating extremely close to the metafrontier for each specific input, suggesting that organic farms' technology is more efficient, as they are operating closer to metatechnology with respect to the management of all inputs. The distance between the metafrontier and group frontier is somewhat large in terms of costs. This implies that a major inefficiency faced by organic farms may lie in the use of fertilizers, pesticides, and water, rather than in labor and trees. In contrast, the

Table 5 Differences in meta-TE and MTR for radial and input use efficiencies: organic versus conventional farms. *Source*: Authors' calculation based on survey data

	Kolmogorov-Smirnov test KS-statistics	Mann-Whitney test Z-statistics	Simar-Zelenyuk adopted Li test Li-statistics
TE with respect to metafrontier			
Radial efficiency	0.259***	− 3.582***	3.362***
	(0.001)	(0.000)	(0.003)
Input use efficiency			
Labor	0.408***	− 6.762***	10.951***
	(0.000)	(0.000)	(0.000)
Paid cost	0.332***	− 5.089***	7.233***
	(0.000)	(0.000)	(0.000)
Tree	0.242**	− 2.721***	0.864
	(0.012)	(0.006)	(0.235)
MTR			
Radial efficiency	0.756***	− 10.697***	1.248*
	(0.000)	(0.000)	(0.065)
Input use efficiency			
Labor	0.667***	− 7.417***	24.813***
	(0.000)	(0.000)	(0.000)
Paid cost	0.810***	− 10.792***	31.897***
	(0.000)	(0.000)	(0.000)
Tree	0.669***	− 9.401***	4.497***
	(0.000)	(0.000)	(0.000)

p-value are in parenthesis.

*, **, *** indicate significant at the 10%, 5%, 1% level, respectively

distance between the metafrontier and group frontier is more remarkable for conventional farms. If conventional farms face no constraints on access to metatechnology, the potential reduction in labor input could amount to 34.2%. Similarly, potential savings in costs could reach 52.6% of input to achieve the best outcome for conventional technology. In sum, organic farms are operating efficiently, close to metatechnology, in the management of all inputs. This is relevant for the use of labor and for tree use in particular.

In Table 3, we compare the TE and MTR between organic and conventional farms. Input use efficiency and its MTR between the two groups are compared in Table 4. Statistical differences between the two groups are not yet tested. While we cannot directly compare the TE with respect to group frontiers, the implemented tests of the computed meta-TE and its MTR are statistically different. Table 5 presents the results of nonparametric tests using the Kolmogorov-Smirnov test, the Mann-Whitney test and the Simar-Zelenyuk adapted Li test. We computed Li test statistics using R software with 1000 bootstrap replications. The original estimates of the meta-TE and MTR are smoothed using Algorithm II (Li 1996; Simar and Zelenyuk 2006). The null hypothesis of the equal distribution of organic and conventional farms was rejected by the Kolmogorov-Smirnov test for both radial efficiency and input use efficiency. We reject the null hypothesis that the two samples are drawn from the same population by the Mann-Whitney test for radial and input use efficiency. Also, the

Simar-Zelenyuk adapted Li test rejects the null hypothesis of equal distributions of meta-TE between the two groups, except for tree use efficiency. These nonparametric test results confirm the significant difference in meta-TE between the two groups. The radial and input use efficiency of labor and cost of organic farms are statistically higher than those of conventional farms. Similarly, Kolmogorov-Smirnov and Mann-Whitney tests reject the respective null hypotheses of radial and input use efficiency for MTR. The Li-statistics suggest the rejection of the null hypothesis of equality of distributions of MTR between the two groups, indicating that the distance from group frontier to the metafrontier is shorter for organic farms compared with conventional farms. This result suggests organic farms are operating closer to the metafrontier than conventional farms.

ESR

The estimated coefficients and robust standard errors from the first and second stages of the ESR models are presented in Table 6. The full information maximum likelihood estimation method is used for estimation, where σ_i is the square root of the variance of the error term in the outcome equations (Eqs. (9a) and (9b)), and ρ_j is the correlation coefficient between the error term of the selection equation (Eq. (8)) and the error term of outcome equations (Eqs. (9a) and (9b)) (Lokshin and Sajaia 2004). The estimated σ_i values are statistically significant in both equations. This suggests the presence of selection bias that stems from unobservable factors. The negative sign of ρ_j for organic and conventional farms suggests the existence of positive selection bias (Oscar et al. 2015; Ma and Abdulai 2016; Lin et al. 2022). This indicates that less efficient farmers are less likely to adopt organic farming and vice versa. The likelihood-ratio test for the joint independence of the three equations produced an insignificant result. As we cannot reject the null of the independence of the equations, this validates the use of ESR rather than the estimation of selection and two outcome equations separately (Loskshin and Sajaja 2004; Oscar et al. 2015). We simply regressed technical efficiency on the adoption of organic farming using the same control variables as those of the ESR. This OLS result suggests that the coefficient is 0.069 and statistically significant at the 5% level. Compared to the estimated ATT from the ESR, the size of the coefficient of organic farming is biased due to unobservable factors. Wald tests assess the joint independence of equations that are statistically insignificant ($\chi^2 = 0.71$, $p = 0.399$). The result validates the application of the ESR method. In the first stage of ESR, the estimated coefficients of access to Canaan Fair Trade and modern olive presses are significant at the 1% level. This result confirms the robustness of using these two instruments. In the selection equation, farm years are positively associated with the probability of adopting organic farming, but the coefficient of its squared term is negative. Farms operating for more years are more likely to adopt organic farming. The likelihood of adoption of organic farming increases when farms have good harvests due to biennial bearing.

Regarding the second-stage results, the following five findings are worth noting. We used the quadratic form for the variable of farmer's age, farming years and age of trees. Accumulation of experience represented by age of head of farm household and years under farming operation may have nonlinear impact on technical efficiency. Similarly, olive yield increases along with age of tress but not continues increasing.

Table 6 Endogenous switching regression estimates on meta-TE. *Source*: Authors' calculation based on survey data

	Adoption of organic farming	TE with respect to metafrontier	
		Organic farms	Conventional farms
Variables	Coefficient	Coefficient	Coefficient
Constant	− 15.8622***	− 0.1117	0.5693***
	(5.0895)	(− 0.1117)	(0.1808)
Family labor	0.0087	− 0.0082	− 0.0082**
	(0.0352)	(0.0053)	(0.0034)
Wage labor	− 0.0319	− 0.0062	− 0.0043*
	(0.0284)	(0.0061)	(0.0024)
Capital-land ratio	− 0.0015	− 0.0007	− 0.0002
	(0.0012)	(0.0006)	(0.0000)
Age	− 0.1166	0.0205	− 0.0007
	(0.0732)	(0.0133)	(0.0062)
Age squared	0.0009	− 0.0002	0.0000
	(0.0007)	(0.0001)	(0.0001)
Education	− 0.0063	− 0.0104**	0.0098***
	(0.0273)	(0.0045)	(0.0026)
Farm years	0.1039***	0.0032	− 0.0047
	(0.0353)	(0.0079)	(0.0043)
Farm years squared	− 0.0015**	− 0.0001	0.0001
	(0.0007)	(0.0001)	(0.0001)
Olive trees	0.0025	− 0.0004	0.0012
	(0.0727)	(0.0194)	(0.0085)
Olive trees squared	0.0031	0.0003	0.0002
	(0.0030)	(0.0008)	(0.0004)
Age olive trees	0.0013	0.0108*	0.0030*
	(0.0217)	(0.0061)	(0.0018)
Age olive trees squared	− 0.0001	− 0.0001*	0.0000
	(0.0002)	(0.0001)	(0.0000)
Share irrigated area	− 0.0049	− 0.0039***	− 0.0006
	(0.0059)	(0.0015)	(0.0008)
Price olive oil	0.0193	0.0087	− 0.0032
	(0.0665)	(0.0145)	(0.0036)
Biennial bearing	0.4734*	0.0449	0.0286
	(0.2617)	(0.0437)	(0.0254)
Distance	− 0.0111	− 0.0062*	0.0066**
	(0.0225)	(0.0033)	(0.0028)
Access to Cannan	3.5504***		
	(0.4018)		
Modern olive presses	0.2701***		
	(0.0705)		
σ_i		0.1682**	0.1558***
		(0.0682)	(0.0538)
ρ_j		− 0.3475	− 0.1906
		(0.4096)	(0.5070)
Log pseudo-likelihood			
Observations	261	80	181

*, **, *** indicate significant at the 10%, 5%, 1% level, respectively. Robust standard errors are in parentheses

First, both family and wage labor in conventional farms negatively affect TE evaluated by the metafrontier, while an increase in labor input has no effect on organic farming. These results imply that the intensive use of labor does not result in improved efficiency. This finding is consistent with the low level of labor use efficacy observed on both types of farms, implying that substantial labor reduction without changing output levels is possible (Table 4). Second, increased years of household head education have a positive effect on the TE of conventional farms but negatively affect organic farms. While an increase in the share of skilled labor has been positively associated with the higher efficiency of olive farms in Tunisia (Lachaal et al. 2004, 2005), a positive effect of farmers' education was not confirmed for Greek olive farms (Niavis et al. 2018). In Turkey's olive sector, the average years of education on farms does not differ between organic and conventional farms, whereas TE is higher for organic farms (Artukoglu et al. 2010). These studies imply that the effect of education on TE is ambiguous. In our case, a positive effect is found for conventional farms but education is not associated with efficiency among organic farms, inferring that organic practice is standardized regardless of farmers' education levels. Third, an increase in the age of olive trees has a positive effect on TE for both farms. This suggests that more mature olive trees are positively associated with improved TE. This result is consistent with the finding on olive farms in Tunisia (Lachaal et al. 2004). In addition, the age of olive trees has a nonlinear effect on organic farms' TE. TE increases with tree age goes up to approximately 54 years, beyond which it declines. Fourth, an increase in the share of irrigated area has a negative impact on the TE of organic farms, suggesting that the expansion of irrigated olive farming area does not result in improved TE. Based on a TE estimation of Spanish olive farms, Tzouvelekas et al. (2001a) found that small farms tend to have higher TE level than large farms for both organic and conventional farming. According to Ahmed et al. (2007), the impact of irrigation on the level of olive production in semiarid areas is positive, but the appropriate quantity of water and periods of irrigation are critical factors that affect productivity. We can infer that it is difficult to attain the best combination of irrigation and organic farming relative to the introduction of irrigation under conventional farming when both techniques are newly introduced. Finally, the distance to the nearest olive oil mill negatively influences the TE for organic farms but positively affects conventional farms. Organic farms located far away from olive oil extraction units are less efficient. This result implies that access to information on organic practice, including oil extraction, may have a positive impact on the TE of organic farming, while it does not improve the TE of conventional farming.

We present the estimation results of ATT and ATU using the ESR models in Table 7. Both organic and conventional farms would benefit from the improvement in TE resulting from the adoption of organic farming, as the estimated ATT and ATU values suggest an increase in TE. Farms choosing to adopt organic farming would have lower TE by 10.7 percentage points had they not adopted this practice. Similarly, the estimated ATU suggests that farms not adopting organic farming would have approximately 8.6 percentage points more TE if they had adopted it. This implies that conventional farms would increase their TE by shifting to organic farming under the given conditions.

Table 7 Average treatment effects: Endogenous switching regression model. *Source*: Authors' calculation based on survey data

Outcome variables	Farm type and treatment effect	Decision stage			
		Adopt	Not to adopt	Average treatment effect	Standard error
Metaefficiency	Organic farms (ATT)	0.698	0.592	0.107 ***	0.016
	Conventional farms (ATU)	0.686	0.600	0.086 ***	0.012

Standard errors were obtained by bootstrapping with 300 replications. *, **, *** indicate significant at the 10%, 5%, 1% level, respectively

Discussion

The National Strategy for the Olive and Olive Oil Subsector in Palestine has been promoting higher productivity, lower production costs, better labeling and organic farming in olive production (MOA 2014b). In line with this strategy, our results suggest that the adoption of organic farming has a positive impact on farms' TE. Specifically, by shifting from conventional to organic farming, TE could be increased by 10.7 percentage points. According to evidence from other countries, the average TE of organic farms in Greece is higher than that of conventional farms, wherein the average TE values are 54.30% and 73.12% for conventional and organic farms in the country, respectively (Tzouvelekas et al. 2001a). The average input-oriented TE for organic farms in Turkey is 67.68%, while it is 47.93% for conventional farms (Artukoglu et al. 2010). While selection bias may exist in these cases, the impact of the adoption of organic farming is valued at approximately 20 percentage points. We controlled for farms' observed and unobserved heterogeneity to reduce selection bias. The magnitude of the impact on TE in the case of Jenin is smaller, but comparable to the above evidence from Greece and Turkey.

While selection bias may remain, the magnitude of the impact of introducing organic farming in Turkey and Greece is roughly double that in Jenin. The average cultivated area in Jenin is smaller, and the level of land productivity is lower than in these two countries. Despite adopting the same modes of organic cultivation, olive farming in Jenin is small in scale and extensive. As annual precipitation is higher in Greece and Turkey, more inputs are required to control pests. In contrast, Jenin is relatively suitable for organic farming with low inputs in nature. Due to such characteristics of olive farming in Jenin, land productivity itself is very low, but the production system provides a more natural environment that is highly compatible with organic farming. Hence, it may be possible to infer that organic and conventional farms have similar characteristics relative to the cases of Turley and Greece, which makes it difficult to realize the large treatment effect of the adoption of organic farming.

Another significant finding concerns the cost-use efficiency of organic farming. In Turkey's case, Artukoglu et al. (2010) reported higher costs of organic farming in terms of labor, fuel, and fertilizer in particular. Conversely, Tzouvelekas et al. (2001a) found that the total costs of organic olive-growing farms in Greece are 11% lower than those of conventional farms. Panagodimou et al. (2019) also demonstrated a lower cost per kg of organic olives in Greece. Our finding of low cost from Jenin is similar to that obtained from Greek olive farms. The total cost decreases by 326 NIS per land as a result of the adoption of organic farming. Organic farming is generally considered to be inefficient and costly (Cobb et al. 1999; Tzouvelekas et al. 2001a; Tzouvelekas et al. 2011b; Mayen et al. 2009); however, we observed a positive impact of organic farming on olive production in terms of both radial and cost-use efficiency. The implication of these findings is that the specific objectives of the national strategy may be made feasible through the promotion of organic farming.

Within the West Bank, Jenin, which is located in the northern part of the territory, has more rainfall than other governorates. Due to its relatively high levels of water availability, it is possible to maintain a certain level of yields without relying heavily on modern inputs such as irrigation, fertilizers and pesticides. While more humid climate conditions generally require the use of pesticides to prevent damage caused by pests and insects, the application of pesticides is not common in Palestinian olive farming. In addition, the dual use regulation imposed on chemical products limits opportunities to use chemical fertilizers and pesticides. Although land productivity is still low in Jenin relative to surrounding countries, climate conditions in Jenin enable to continue extensive, low input forms of olive production including organic farming.

Why is organic olive farming more productive and less costly than conventional farming? According to interpretations offered by Tzouvelekas et al. (2001a) regarding Greek olive farms, a lower profit margin for organic farmers may force them to become more efficient. Another possible reason is that organic farmers have become more cautious in their selection of inputs due to restrictions imposed by European Union (EU) Regulation 2092/91 regarding the types of fertilizers and weed/pest control that can be used. In Jenin, the Canaan Fair Trade organization provides strong support and training to help farms adopt organic methods and produce value added organic products. Olive products transacted by the Canaan Fair Trade association undergo quality control to be certified as Fair Trade products and most are certified as organic by the United States Department of Agriculture. Therefore, similar to Greek farmers, farmers in Jenin must be careful about their choice of inputs to comply with quality assurance regulations.

With respect to pest control, olive production in the West Bank may somewhat differ from the intensive modern farming observed in EU countries. According to Beaufoy (2001), there are three main types of olive plantations: low-input traditional plantations with scattered trees, intensified traditional plantations, and intensive modern plantations. In the EU, while the European Commission's Regulation (EC) 848/2008 tightened restrictions on the use of pesticides and fungicides, olive pest and disease management strategies are still based on the use of chemical pesticides (EC 2007). In the Mediterranean region, approximately 30% of olives produced are lost to pests and diseases; the cost of controlling these pests and diseases exceeds 200 million euros annually, with half of this amount spent on insecticides and fungicides (Fernández-Escobar et al. 2013). The olive fly (*Bactrocera oleae*) is a typical insect pest and is especially problematic in more humid, frost-free areas (Beaufoy 2001; International Olive Council 2007). Applying pesticides and chemical fertilizers with a higher tree density (200–400 trees/ha) is quite common for intensive modern plantations. Following Beaufoy's (2001) classification, our sample farms in Jenin can be categorized as intensified traditional plantations rather than intensive modern plantations. In Jenin, the percentage of farms that use pesticides remains at 18.3% of the total and reaches only 22.6% among conventional farms. These figures imply that pesticide use is not a common practice on these farms. This relatively low use of pesticides may be due to the climate conditions in Jenin, which is less humid than coastal regions, particularly during the dry season. Since the olive fly tends to be much less prevalent in dry, high-altitude areas (Beaufoy 2001), the cost of pesticides can be avoided. Therefore, the climate conditions for organic olive farming may be favorable as long as intensive traditional plantations continue operating.

Comparing the costs of organic and conventional farms, the average operational cost and wage cost are higher for conventional farms (Table 2), inferring that the higher wage cost for conventional farms may be attributed to the use of more inputs; namely, fertilizer and pesticides, which require labor input. However, despite the intensive allocation of agricultural inputs using wage labor, the labor and cost use efficiency of conventional farms is significantly lower than that of organic farms (Tables 4, 5). Similarly, our ESR estimations suggest that the TE of organic farms would be lower had they not adopted organic farming (Table 7). These figures imply that organic farms spend more on wage costs but are more productive due to their efficient use of other inputs. In contrast, conventional farms use more agricultural inputs at the expense of wage costs but do not realize higher productivity. Therefore, inefficiencies may exist in conventional farms in terms of using fertilizers, pesticides, and wage labor. Evidence of conventional farms having lower TE than organic farms is also observed in Greece and Turkey (Artukoglu et al. 2010; Tzouvelekas et al. 2001a).

Throughout the Palestinian territory, the diffusion of organic farming remains underdeveloped relative to that in other countries in the Mediterranean region. The area covered by organic farming remains at 7.5% in Palestine compared to levels of 27.3% and 20.2% in France and Italy, respectively (Willer and Lernoud 2019). The positive impacts of organic olive farming suggest significant potential to increase productivity by expanding organic farming; however, the rate of organic farming adoption in our sample is 30.7%, which is already much higher than the aforementioned averages for France and Italy. Despite the higher diffusion of organic farming in Jenin, TE is generally low relative to levels in Greece and Turkey (Tzouvelekas et al. 2001a; Artukoglu et al. 2010). However, we found that olive farms can reduce inputs by 37.0% without changing output. These results imply that there is considerable potential for improvement in the efficient use of inputs and considerable room for improvement in olive production.

Conclusion

This paper investigates the effect of organic farming adoption on the TE of olive production in Jenin of the West Bank. We employ a metafrontier model with a directional distance function and DEA approach and ESR to control the selection bias caused by farms' unobservable characteristics. The results suggest that olive farms in Jenin have the potential to reduce inputs by 37.0% with given inputs and technology while maintaining current output. Organic farms operate closer to their own production frontier than conventional farms, and closer to metatechnology than conventional farms with respect to radial and input use efficiency. The estimated ATT and ATU values suggest that the adoption of organic farming has a positive impact on TE. Organic farms would have 10.7 percentage points less TE had they not adopted the organic farming method.

Likewise, conventional farms can improve their TE by 8.6 percentage points shifting to organic farming. Our results suggest that organic farming is not cost-inefficient and has the potential to improve TE through an efficient use of agricultural inputs.

Despite this evidence of organic farming's positive impact, this study has certain limitations. First, to determine the treated group of farms adopting organic farming, we depended on farmers' self-declarations rather than on organic certifications. Endogenous bias was mitigated by using the ESR method, yet bias may still remain due to this self-declaration approach rather than the use of an exogenous condition, such as evaluation by a certifying organization. Second, the sample used in this study was limited to Jenin, where organic farming is relatively active. This may be attributed to the influence of the Canaan Fair Trade organization's activities. Empirical results from Jenin must be treated with caution as they are based on a single study in a specific region and may not be applicable to other governorates. Nevertheless, assuming the absence of strong interactions between regions, i.e., the homogeneity of olive farms within a region, our findings imply that the adoption of organic farming can be an effective means of improving the TE of olive production. Even if opportunities for horizontal land expansion are limited, olive farms have the potential to improve their productivity by more efficient use of inputs. Organic farming would bring olive farms closer to their efficient frontier under severe constraints. This evidence may also be relevant to small farmers in the West Bank under occupation.

Appendix

See Tables 8, 9.

Table 8 Parameter estimates: Test on the validity of the selection instruments. *Source*: Authors' calculation based on survey data

Variables	Adoption of organic farming	Metaefficiency of conventional farms
	Coefficient	Coefficient
Constant	− 39.3032***	0.9437***
	(13.9383)	(0.2891)
Access to Cannan	6.8116***	0.1225
	(1.1695)	(0.0891)
Modern olive presses	0.6339***	− 0.0054
	(0.1978)	(0.0042)
Control variables	Yes	Yes
Log pseudo-likelihood	− 66.58	
Wald $\chi^2_{(2)}$	44.88***	
F-statistics		2.080
R^2		0.187
Pseudo R^2	0.586	
Observations	261	181

*, **, *** indicate significant at the 10%, 5%, 1% level, respectively. Robust standard errors are in parentheses

Table 9 Average treatment effects: Endogenous switching regression model using instruments with heteroscedasticity. *Source*: Authors' calculation based on survey data

Outcome variables	Farm type and treatment effect	Decision stage			
		Adopt	Not to adopt	Average treatment effect	Standard error
Metaefficiency	Organic farms (ATT)	0.698	0.579	0.119***	0.017
	Conventional farms (ATU)	0.690	0.599	0.091***	0.013

We estimated the ESR using the instruments with heteroscedasticity proposed by Lewbel (2012, 2018a, 2018b). Following empirical application by Lin et al. (2022), we run the regression of the endogenous variable (adoption of organic farming) on the exogenous variable $\boldsymbol{Z}_i$ and predict error term e_i. Then, instrumental variables are constructed as $\left(\boldsymbol{Z}_i - \overline{\boldsymbol{Z}}\right)e_i$, where $\overline{\boldsymbol{Z}}$ is the sample mean of $\boldsymbol{Z}_i$. The elements of $\boldsymbol{Z}_i$ are all control variables from Eq. (8). This method assumes that residual e_i is supposed to be heteroscedastic. Standard errors were obtained by bootstrapping with 300 replications.

*, **, *** indicate significant at the 10%, 5%, 1% level, respectively

Abbreviations

ATT	Average treatment effect on treated
ATU	Average treatment effect on untreated
DEA	Data envelopment analysis
DMU	Decision-making unit
ESR	Endogenous switching regression
GAMS	General Algebraic Modeling System
MOA	Ministry of agriculture
MTR	Metatechnology ratio
NGOs	Nongovernmental organizations
OLS	Ordinary least squares
PSM	Propensity score matching
TE	Technical efficiency
VRS	Variable returns to scale

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KK is involved in conceptualization, methodology, data collection, cleaning, analysis, and writing the original manuscript. HK is involved in conceptualization, data analysis, editing the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets used and analyzed during the current study are available from corresponding author on reasonable request.

Declarations

Competing interests
The authors declare no conflict of interest.

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