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# Towards a comparative analysis of olive farmers' technical efficiency: Lessons from Data Envelopment analysis and Fuzzy-set Qualitative Comparative Analysis on small olive farms in Tunisia

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### Abstract

Considering the economically, socially, and culturally vital character of olive growing in Tunisia, and the very significant proportion of small farmers operating in this sector, especially in rural areas of this country, there is a strong case to examine the performance of small olive farmers in such regions. To do so, this paper uses Data Envelopment Analysis (DEA) to assess small Tunisian olive farmers' efficiency and combines symmetric techniques (OLS and Tobit regressions) with asymmetric technique (Fuzzy-set Qualitative Comparative Analysis (fsQCA)) to identify the main antecedents that might explain the gaps in efficiency among them. The results reveal that there is substantial room for improvements of the technical efficiency of these farmers. Moreover, the regression models show that four determinants individually explain gaps in efficiency among farmers: age, education, access to agricultural credit, and ownership status. The fsQCA results provide four different combinations of conditions leading to high levels of olive farmers' efficiency. They also highlight the strong causal relationship (core conditions) between olive farmers' efficiency and two antecedents in particular: farmer's level of education and ownership status of the land devoted to olive-tree cultivation. This study also provides some valuable policy and managerial implications for farmers, central and regional government agencies promoting and supporting agriculture, and policy-makers.

***Keywords***: *Olive farmers' efficiency, DEA, fsQCA, Small farms, Tunisia.*

**JEL Classification**: Q12, R11, L25, C14, C21, N57

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## 1 INTRODUCTION

Tunisia's agricultural system is based on small family farms, which represent 78% of the total number of farms. This small-scale agriculture plays a crucial role in employment generation and income opportunities, especially in rural areas (Food and Agriculture Organization (FAO), 2017). Consequently, one key objective of the Tunisian agricultural policy is to enhance the productivity of these small farms to promote agricultural development and improve living conditions in rural and remote areas in the country (International Fund for Agricultural Development (IFAD), 2019).

Olive production is one of the priority target sectors, as it is vital to the country's economy. Indeed, most of the agriculture area in Tunisia is planted with olive trees (102,4 million olive trees),



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representing approximately 82% of the total area planted with arboricultural trees in the country (National Observatory of Agriculture (ONAGRI), 2021; Statita Research Department, 2021). Moreover, Tunisia is one of the main largest producers of olives and olive oil in the world. In 2020, this country was ranked the second world producer of olives and olive oil after Spain, with 350 000 tons of olive production, and 400 000 tons of olive oil (accounting for 12.5% of the worldwide olive production in 2020) (ONAGRI, 2021; Statita Research Department, 2021). Olive oil constitutes the most significant part of the Tunisian agricultural exports, with nearly 40% of the country's total agricultural exports (Statita Research Department, 2021). Finally, economically and culturally, olive production remains the main agricultural activity for 310 000 olive farmers (about 60% of the total number of farmers) (ONAGRI, 2021). Additionally, for over a millennium, this agricultural activity has been considered an integral part of the Tunisian culture, habits, and history (Neves & Pires, 2018).

As argued by Colombo & Perujo-Villanueva (2017, p. 226), small olive farms are generally subject to diverse ″pressures due to several interacting causes″. Tunisian olive small-scale farms are no exception. They are often confronted with several severe constraints that drop their productivity and reduce their profit margin (FAO, 2017). These constraints can be categorized into four categories: climatic, political, institutional, and technological. Firstly, regarding climatic constraints, agriculture in Tunisia is regularly subject to the chronic problem of water scarcity, rainfall deficits, frequent drought episodes, land degradation, continued expansion of desertification, groundwater overexploitation, etc. (Soltani & Mellah, 2023). These problems are exacerbated by the fact that three quarters of Tunisia's territory are semi-arid or arid (Ben Hassine et al., 2017). Secondly, as for the political constraints, Tunisia has experienced major socio-economic transformations since January 14, 2011, with the advent of the so-called "Jasmine revolution" which led to the fall of the former president Zine al-Abidine Ben Ali (Gana, 2012). This transition has resulted in socio-economic difficulties, especially in rural and interior regions, notably excess borrowing, a rise in the unemployment rate, a growing commercial balance deficit, an increase in essential food prices, broadened social and regional disparities, and corruption (Enwere, 2021). Thirdly, the panoply of constraints discussed above has been exacerbated by several institutional ones, such as the limited access to agricultural credit facilities (Dhehibi et al., 2022), the weakness of farmers' organizations (Dhehibi et al., 2022), and the poor availability of social services and basic infrastructure in rural areas (e.g., education and training programs, health services, etc.) (Mhadhbi & Napoléone, 2022). Finally, regarding technological constraints, 80% of the rural farmers in Tunisia rely on traditional agricultural production practices and methods of cultivation (Dhehibi et al., 2022). This constitutes a major obstacle to performance improvement, notably due to the inefficient use of resources or the low adoption of new technologies and innovative methods (Dhehibi et al., 2022). All these environmental, political, institutional, and technological constraints are exacerbated by the fact that most of the olive farmers are illiterate and non-owners of the lands they exploit (Hammami & Ferchichi, 2023). Consequently, they remain caught in poverty traps and are unable to achieve significant economic gains (Gana, 2012). Considering the economically, socially, and culturally vital character of olive growing in Tunisia, and the very significant proportion of small farmers operating in this sector, especially in the rural areas of this country, there is a strong case to examine the performance of small olive farmers in such regions (Fernández-Uclés et al., 2020; Lachaal et al., 2005).

This study provides several significant and original contributions. Firstly, despite the consolidated literature on the assessment of efficiency in agriculture, a small number of studies have dealt with the efficiency in the olive sector, particularly in Tunisia (Dhehibi et al., 2007; Fernández-Uclés et al., 2020; Kashiwagi et al., 2016; Kamiyama et al., 2021; Lachaal et al., 2005). Secondly, to our knowledge, this is the first study that combines symmetric (OLS and Tobit regressions) and



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asymmetric (fsQCA) techniques to identify, respectively, predictors of olive farmers' efficiency, and configurations of causal conditions that lead to the efficiency of these farmers. It is worth noting that the study of Fernández-Uclés et al. (2020) that combined DEA and FsQCA was not attempted to assess efficiency of olive farms, but companies dedicated to the activity of olive oil marketing. Several experts on QCA techniques recommend combining this method with correlational techniques to enhance the robustness and reliability of the obtained findings (Ragin, 2008). Thirdly, the majority of prior studies assessing technical efficiency in olive sector choose in ad hoc manner the determinants that might explain farmers' gaps in technical efficiency, while those considered in this study are grounded in a widely recognized theory in the field of strategic management: the resource based-view theory of the firm (RBV). Finally, this study focuses on a subsample of small farmers who are highly dependent on this sector and where the reality is exacerbated by several environmental, political, institutional, and technological constraints. The study's findings will propose evidence-based courses of action for decision-makers to promote and support the small-scale farmers operating in the olive sector. Thus, olive farmers will be able to increase their competitiveness, profits, and ultimately enhance their living standards.

The remainder of this paper is organized as follows. In Section 2, we introduce the economic concept of technical efficiency and provide an overview of the literature on the measurement of olive production efficiency, as well as its antecedents. Section 3 provides the analytical approach adopted in this study, namely the Data Envelopment Analysis (DEA) approach, and the Fuzzy-set Qualitative Comparative (fsQCA) approach. Section 4 describes the study's context, presents information on questionnaire development, sampling, data collection procedure, and empirical findings. Finally, Section 5 concludes by discussing both implications for olive farmers and public policy, and the limitations of the study.

## 2 THEORETICAL BACKGROUND

The study of efficiency measurement is under great scrutiny. It was initiated by the pioneering work of Koopmans (1951) and Debreu (1951). These works have then been empirically applied by Farrell (1957) in a path-breaking paper. According to Farrell (1957), two distinct types of efficiency exist: allocative efficiency (AE) (reveals the resource-use performance) and technical efficiency (TE) (reveals the technological performance). The product of both technical and allocative efficiencies is the economic efficiency (EE). Technical efficiency is a concept fundamentally grounded in neoclassical production theory, which stands as a cornerstone (Sickles & Zelenyuk, 2019). At the core of this theory lies the concept of the " frontier production ", that expresses the relationship between inputs and outputs within the production context. An assessment of technical efficiency is achieved through the estimation of the frontier production function, which can be either parametric or non-parametric (Aigner et al., 1977). This function is a mathematical representation connecting all efficient production points (Charnes et al., 1978; Forsund et al., 1980). This implies that a production unit is considered technically efficient when positioned on the "production frontier". In different words, Production units located on this frontier are operating at their utmost potential. This suggests that they strive to produce the greatest possible output from a given set of inputs, or conversely, they strive to utilize the least possible inputs for a given level of output (Koopmans, 1951). The gap between the production frontier and observed production units serves as an indicator of each unit's efficiency level. This enables the identification of the most efficient producers, those situated on or closest to the frontier, as well as the less efficient ones, which exhibited a greater distance from it (Kumbhakar et al., 2020). Generally, there is a three-stage procedure to explore in-depth how efficiency is defined, measured, and assessed. The first stage consists in choosing an approach for the measurement of the



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efficiency frontier. In the second stage, the inputs and outputs, that can most appropriately explain the inefficiency, are identified, based on the relevant literature on the topic. Finally, the third stage consists in deciding which analytical techniques will be used to examine the gaps in the technical efficiency scores, and which factors might explain these gaps (Amara et al., 2020).

### 2.1 Step procedure of measuring and analyzing technical efficiency

*Step 1: Choice of the Efficiency Assessment Approach*

The two main approaches to generate efficiency measures based on the production frontier function are the deterministic approach and the stochastic approach. In the former, all firms share the same production frontier technology. Thus, any deviation from the production frontier is attributable to inefficiencies in input use. Depending on whether its relation to the production inputs is implicit or explicit, this frontier may be nonparametric or parametric (Farrell, 1957). As argued by Forsund et al. (1980), the deterministic approach ignores the fact that farm's performance may be affected by factors that are beyond its control such as bad weather, poor performance of the machinery or breakdowns in the input supply. Thus, deviations from the efficient frontier may be of two origins: inefficiency in input use or random variations in the frontier across different farms. The stochastic frontier or the composed error model introduced by Aigner et al. (1977) and Meeusen & Van Den Broeck (1977) accounts for such occurrences. Indeed, the deviation from the efficient frontier is decomposed into two components: a symmetric random component that captures the effects of factors beyond the farm's control, and a one-sided component that accounts for technical inefficiency. The main disadvantage of the stochastic approach is the necessity to impose a stringent parametric structure on the specification of production function and on the distribution of efficiency. Nevertheless, the two approaches provide a single dimensionless overall index of efficiency. This index may be applied to an individual unit of production, ranking only its own relative performance over time or relative to a group of units of production, evaluating their relative performance during one or several periods of time.

Two main techniques are commonly used to estimate production frontiers: mathematical programming approach and the econometric approach. The former is based on the application of non-parametric linear programming tools to assess the efficiency of a DMU relative to similar DMUs. Data envelopment analysis (DEA) is the most used tool of this approach (Charnes et al., 1978). While the latter uses econometric techniques to estimate a stochastic frontier function. The detailed mathematical development and specificities of each of these two approaches, as well as the comparison of their advantages and limitations, are consolidated and well documented in ten of the previous studies (see, for instance, Kumbhakar et al., 2020). With regard to the olive sector, several studies have been conducted to assess the efficiency of olive farmers around the world (Amores & Contreras, 2009; Artukoglu et al., 2010; Beltrán-esteve, 2013; Bernal Jurado et al., 2017; Giannakas et al., 2000; Kourtesi et al., 2013; Lambarraa et al., 2007; Niavis et al., 2018; Raimondo et al., 2021; Stillitano et al., 2019), and in Tunisia in particular (Dhehibi et al., 2007; Kamiyama et al., 2021; Lachaal, 2005). In this study, we will use DEA to generate efficiency scores of Tunisian olive farmers composing our sample. Two main reasons justify our choice of DEA at the expense of SFA. Firstly, as argued by Katharakis et al. (2014, p. 345), "*DEA has the advantage that it is able to manage complex production environments*." Indeed, the non-parametric structure of DEA does not impose a functional form on the production frontier and hence can accommodate wide-ranging behavior. This is of great importance when the usual axioms of production activity may break down (i.e., profit maximization). This might be the case of the very small farmers composing our sample that are facing



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many constraints and not necessarily driven by profit maximisation objectives. Thus, the imposition of only a few restrictions on the data is likely to be more attractive (Amara et al., 2020). Secondly, the SFA approach estimates simultaneously the efficiency scores and the sources of inefficiency that are generally concerned with the role of farm and farmers' characteristics. Hence, the obtained efficiency scores are in some ways moderated by the variations in the predictors of farmers efficiency scores. As we aim to consider such predictors as conditions in our fuzzy-set analysis with efficiency scores as outcome, the one-step estimation procedure of SFA is less attractive for our case. In contrast, the DEA approach enables obtaining, in a first stage, efficiency scores that are independent from the predictors of inefficiency. These scores are thereafter considered in a second stage as a dependent variable in a regression relating it to a set of potential predictors of inefficiency among farmers composing our sample. The assessment of the gap in efficiency among farmers is therefore carried-out for both regression and fuzzy-set analysis on efficiency scores that depend only on output and inputs.

*Step 2: Specification of Outputs and Inputs*

The review of the literature on the efficiency of agricultural productions in general and the efficiency of olive farmers in particular enables to identify the variables that are recurrently considered as outputs and inputs of the olive production. In this paper, following the specification of outputs and inputs by many authors, we consider one output and three inputs to feed the DEA model. Indeed, in most previous studies, the amount of olive production per campaign is the measure considered to operationalize the output of the olive production activity (Lachaal et al., 2005). As for the inputs, the farm's total land devoted to olive-tree cultivation is one of the main factors of production in agriculture. In olive production, it corresponds to the olive cultivated area of the farm (Stillitano et al., 2019). Likewise, regarding the second input, the amount of fertilizers used, it is generally expressed by the quantity of mineral and organic fertilizers, as well as phytosanitary products, chemical pesticides, etc. However, due to the low use of fertilizers in olive production, we only consider mineral and organic fertilizers in our model. Several authors have included fertilizers as an input in their assessment of the technical efficiency of olive farmers (Lambarraa et al., 2007). Finally, regarding the third input, namely the workforce employed in olive production activities, several measures of the labor input were proposed in the previous studies. The most recurrent operationalizations expressed this input in terms of labor costs (Artukoglu et al., 2010), or the number of working days or hours of work (Beltrán-Estevea, 2013). It is worth noting that the capital factor was not considered as an input in this study, since we are only focussing on small-scale olive farms, generally characterized by a low capital-intensive agricultural infrastructure and equipment.

*Step 3: Determinants of Olive Farmers' Inefficiency*

To investigate why some farmers are more likely to reach higher efficiency levels than their counterparts, we drew in the resource based-view theory of the firm (RBV) (Barney, 1991; Penrose, 1959; Prahald & Hamel, 1990; Teece et al., 1997; Wernerfelt, 1984). RBV stands as *"one of the most widely accepted theoretical perspectives in the strategic management field*" (Newbert, 2007, p. 121). It provides a framework for linking resources at the disposal of the firm to its performance. Edith Penrose is recognized as the pioneer to putt forward the importance of resources to a firm's competitive position. In her seminal work published in 1959, she argued that a firm consists of "*a collection of productive resources"* (Penrose, 1959, p. 24), that should be well exploited to contribute to its competitive advantage. Several subsequent developments of RDV theory were undertaken notably during the 1990s. Among them, the influential works of Barney (1991) and Teece et al. (1997). The former proposed the Barney's VRIO framework that is a strategy tool that enables firms



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identifying the resources and capabilities that gives them a sustained competitive advantage. Resources and capabilities could be financial, human, organizational, physical, or technological in nature. Barney argued that in addition to having valuable, rare, inimitable resources, "*a firm also needed to be organized in such a manner that it could exploit the full potential of those resources if it was to attain a competitive advantage*" (Barney, 1997, p. 160, quoted by Newbert, 2007, p. 124). The latter proposed a new theoretical approach that more specifically defined the types of processes by which firms could exploit resources. Indeed, the paper of Teece et al. (1997) introduced the concept of dynamic capabilities defined as *"the firm's ability to integrate, build and reconfigure internal and external competences to address rapidly changing environments*" (Teece et al., 1997, p. 516). Dynamic capabilities were the pivotal concept of their framework attempting *"to explain how combinations of competences and resources can be developed, deployed, and protected*" (Teece et al., 1997, p. 510). RBV has undergone some other development and refinements over the two last decades, evolving gradually from a conception that considers resources as a static list of the ingredients to a dynamic conception focussing on the process by which these resources must be utilized to ensure competitive advantage for the firm. Moreover, it is now well understood that "*in addition to possessing these ingredients, firms seeking a competitive advantage must also demonstrate the ability to alter them in such a way that their full potential is realized*." (Newbert, 2007, p. 124). Numerous previous studies were grounded in the RBV theory to explain the differences in firm efficiencies and emphasized the potential for building competitive advantage through benefits stemming from firm-level efficiency advantages (Teece et al., 1997). This stream of research contends that the different bundles of resources and capabilities available for firms explains why some are more efficient than others (Moradi et al., 2021). The RBV theory is ideally suited to our subject of study as it enables predicting the relationship between the farm's resources and capabilities and its efficiency. Therefore, we assume that olive farmers use a great number of idiosyncratic resources and capabilities which are deployed and mobilized in olive production. Such a perspective suggests that farmer's efficiency will increase when the mobilization of the resources and capabilities on their disposal will be appropriate. It also suggests that the success of mobilizing and allocating resources and capabilities might differ among farmers, which might create gaps in terms of level of efficiency between them. Based on this rational, we considered five predictors of the gaps in efficiency among olive farmers that are recurrently included in the models attempting to identify the predictors of technical efficiency in olive production. These predictors represent different resources and capabilities that are influential on the farmers levels of efficiency: 1) farmer's age; 2) farmer's educational level; 3) farmer's access to agricultural credit; 4) off-farm income; and 5) the status of ownership of the land dedicated to olive production.

- Farmer's Age as a Proxy of his/her Capital of Experience in the Olive Production Sector

When considering the impact of farmer's age on his/her capacity to optimally allocate the bundle of inputs at his/her disposal to produce olives, the findings of many previous studies revealed that older farmers are more efficient than younger ones. According to authors such as Giannakas et al. (2000), and Lambarraa et al. (2007), older farmers are more likely to have a cumulative farming experience allowing them to have better farm-level decision-making, more adequate equipment and machines, better networks of clients and suppliers, and better access to labour than the younger farmers. On this matter, Paul (2023, p. 15) contended that: "*The traditional cultivation method demands a sound knowledge of the various activities involved in the production process. An aged grower enjoys more knowledge, experience and strong business connections that eventually help the optimum allocation of resources*". This might be also attributable to the lack of attractiveness of the rural lifestyle for the younger farmers (Martín et al., 2017), and the off-farm employment opportunities as a pathway to a



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better livelihood (Gana, 2012). In contrast, the findings of some other studies showed that, on the contrary, young farmers should be more efficient compared to older ones as they are more likely to integrate new information and communication technologies (ICT), to assimilate new farming practices, and to adopt new agricultural innovations (such as drones that collect and plot weather data, automated systems, robotics, geomatic technologies, etc.). From this standpoint, contrary to older farmers who are more likely to rely on traditional agricultural practices, tend to be more risk-averse, and late-adopters of new agricultural technologies, the younger farmers are more willing to contribute to the renewal of farms and to rapidly incorporate the technological changes in their farming activities (Lambarraa et al., 2007). Hence, to consider the findings of these two opposing streams of studies, we contend that the impact of age on farmers' efficiency is an empirical matter. Thus, we hypothesize that:

***H*$_1$**: *The farmer's age may impact positively or negatively his technical efficiency in small-scale olive farms in the rural regions of Tunisia.*

- Farmer's Educational Level as a proxy of his/her Capacity of Absorption of Knowledge

Previous studies are less controversial about the impact of farmers' level of education on their technical efficiency scores. Indeed, the positive impact of education on olive farmers efficiency is well documented in the literature (Giannakas et al., 2000; Lachaal et al., 2005). This implies that higher-educated farmers are more efficient than illiterate or less educated ones. Indeed, educated farmers could better perceive the farming information (including the latest information on weather hazards, the prices of agricultural inputs, the state of technology, and the better agricultural methods) and be more able to integrate it in their farming activities to make better decisions on the optimal use of agricultural resources (seeds, fertilizers, agrochemicals, mechanization, etc.). They also tend to undertake more risky activities than their counterparts and to adopt more rapidly new and more productive technologies. According to authors as Rodrigues et al. (2023), farmers with a higher level of education are expected to have better knowledge about technological innovations. Consequently, they are more likely to adopt them than farmers with a lower level of education.

***H*$_2$**: *The greater the farmer's level of education, the greater his level of technical efficiency in small-scale olive farms in the rural regions of Tunisia.*

- Access to Agricultural Credit as a Proxy of his/her Capacity to Raise Financial Resources

A dominant stream of studies has identified a positive relationship between the access to agricultural credit and the efficiency of farms (e.g. Marzin et al. 2017). In fact, the availability of financial resources might offer the smallholder farmer the opportunity to invest in farm infrastructure, procure modern inputs, finance additional work labour, adoption of productive technologies, reduce the risks and unforeseen expenditures, as well as to better fulfill the production objectives (Rodrigues et al., 2023). However, other studies have reported that access to credit may have a negative effect on the efficiency level (e.g. Tenaye, 2020). The credit risk management could render the small-scale farmers inefficient since it leads to enlarge debt burden, to potentially restrict the farmers' maneuverability and to limit the introduction of improvements and changes in farm management processes. Notwithstanding these counterintuitive findings of these studies, we assume, in this paper, that farmers who have access to agricultural credit would be more efficient than those who have limited or no access.

***H3:*** *Access to agricultural credit has a positive impact on the technical efficiency in small-scale farms olive in the rural regions of Tunisia.*



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- Farmer's Off-farm Income as a Proxy of his/her Capacity to Generate Additional Financial Resources

Many previous studies have reported that the off-farm income contributes to the improvement of farmers' efficiency (Paul, 2023). In that vein, the involvement in casual or permanent off-farm activities is a way for small-scale farmers to generate supplemental income that may contribute to cover a part of the agricultural expenses. In fact, given the inherent risk of agricultural production and in-farm incomes (poor harvests, droughts, diseases, etc.), many small farmers tend to opt for income diversification as a management strategy to minimize production losses and other related farming risks, as well as to ensure a certain stability of their income (Pfeiffer et al., 2009). Hence, the off-farm work offers a form of security for farmers enabling them to remedy the shortage of financial resources during tough crop seasons. However, some other studies have shown that the farmers' involvement in off-farm activities might have a negative impact on the farm efficiency level. The off-farm work is generally done at the expense of the time normally devoted to farming activities. This could be detrimental to the course of schedule and the right timing of agricultural activities. This may lead to less informed managerial decisions, a misallocation of resources, and consequently to a decrease in efficiency (Harmini et al., 2022).

Notwithstanding these counterintuitive findings of these studies, we assume, in this paper, that farmers who generate off-farm income would be more efficient than those did not generate off-farm income. Thus, we hypothesize that:
***H$_4$**: The off-farm income impacts positively the technical efficiency in small-scale olive farms in the rural regions of Tunisia.*

- Land Ownership as a Proxy of his/her Capacity of Having Collateral Warranty

Prior studies have argued that access to land ownership, also referred as the land tenure security in the literature, can positively affect the small-scale farmers' efficiency (Ngango & Hong, 2021). Indeed, farmers adopt distinct logics depending on their property status. Landowner farmers find themselves in need of securing a long-term agricultural investment and of managing the farm's activities for a long-time horizon. Therefore, they are more likely to intensify cultivation, use more efficiently productive resources, acquire new equipment, and are more willing to adopt new technologies that improve agricultural productivity. Moreover, can also be used as collateral warranty with credit providers to obtain loans. On the contrary, producers who operate farms as tenants are mainly motivated by shot-time profit and less likely to implement long-term agricultural improvements (Olagunju et al., 2023). Thus, based on this rationale, we hypothesize that:
***H5:** Property status has a significant positive effect on the technical efficiency in small-scale olive farms in the rural regions of Tunisia.*

## 3 RESEARCH OBJECTVE, CONTEXT OF THE STUDY, DATA AND METHODOLOGY

### 3.1 Research Objective

Using a sample of Tunisian small olive farmers, this study attempts to assess the efficiency of olive production. More specifically, this paper addresses two questions: (1) how efficient are Tunisian small



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olive farmers? and (2) what are the main antecedents that might explain the gaps in the efficiency among them?

### 3.2 Context of the Study

This study was carried out in the rural region of Chebika situated a few kilometers from the city of Kairouan in the center of Tunisia. It is considered a gateway between the northern and southern parts of the country. The region of Chebika belongs to the plain of Kairouan with an agricultural area of 51 280 hectares. This region is characterized by significant rainfall fluctuations and temperature changes. The average temperature of the whole region is between 5 and 21°C in winter and between 25 and 42°C in summer. The minimum temperature can go down to - 3°C in winter, while the maximum temperature can easily reach +46°C in summer (Commissariat Régional au Développement Agricole (CRDA), 2014). The region of Chebika is among the least rainy regions in Tunisia with an annual average rainfall of 200 to 250 mm. The phenomenon of overexploitation of the groundwater remains a chronic issue in this region, due to the persistent disequilibrium between the amount of water withdrawn and the amount of water available. According to the data collected from the CRDA of Chebika (2014), the total agricultural area encompasses 51 280 hectares. Among this area, 9 500 hectares remain uncultivated, while 41 780 hectares are designated as usable agricultural land. The economy of the Chebika region is mainly based on the agricultural sector. The agricultural structure is dominated by small-scale farms with a surface area of less than 10 hectares. However, while farms occupying less than 5 hectares constitute 70% of the total farm count, they only cover 29% of the total surface area (CRDA, 2014). The main component of the cropping system is arboriculture, mostly dominated by the olive trees, which covers 80% of the irrigable area (CRDA, 2014). The olive trees blanket more than two-thirds of the arboriculture area. In response to the need for increased income and familial support, farmers in the region often engage in intercropping various crops, such as market vegetables and cereal monocultures, often in conjunction with temporary or permanent livestock.

### 3.3 Questionnaire, Sample, and Data Collection

The questionnaire was developed by conducting a focused literature review on the measurement and determinants of efficiency in the agricultural domain in general and in the olive sector in particular. We mainly targeted two databases, namely ISI Web of Science and EBESCO/ Academic Search Premier, to identify various measures and indicators used in prior studies to operationalize the outputs, inputs, and antecedents of olive production. To perform our search in these databases, several relevant keywords (e.g., olive farmers, olive producers, olive production, developing countries, Data Envelopment Analysis (DEA), Qualitative Comparative Analysis (QCA), fuzzy-set Qualitative Comparative Analysis (fsQCA), measurement, assessment, evaluation, scale, construct, survey) were combined with keywords such as production function, productivity, technical efficiency, outputs, inputs. On the basis of the existing scales and findings of the focused literature review, and after several iterations, we generated 75 questions grouped into four sections: 1) production of olives and other crops, and livestock; 2) inputs mobilized to produce olive; 3) determinants of variations of efficiency in the olive production sector; and 4) socio-economic characteristics of farmers (e.g., age, gender, marital status, educational status, access to credit, other sources of income, duration in olive production activities), and characteristics of farms (e.g., size, ownership status, production diversification). The individuals composing the population of this study are the olive farmers in the rural region of Chebika in Tunisia, operating farms of less than or equal to 10 ha. This choice is justified by the dominance of this stratum with 70% of the total of olive farms in Chebika (CRDA, 2014). We relied on four complementary approaches to identify this population and collect data.



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Firstly, a documentary search was conducted to identify documents and reports from the Ministry of Agriculture, the technical services of the Commissariat Régional au Développement Agricole (CRDA) and the National Institute of Statistics (INS). The collected information relates to the general context of olive production, the situation of olive producers, and the olive sector in the region under study, Chebika, and in Tunisia in general. Secondly, we contacted the CRDA to help us identify the population of olive farmers in the region and establish a first contact with them, to gauge their interest in participating in our field survey. We received great logistical support from this agency that made contacts with the producers, accompanied us, and introduced us to them during the interviews. Two representatives of the agency ensured our travels through the various selected farms. Their presence created a climate of trust since the producers already knew them. Thirdly, according to the available data provided by the CRDA, the total population of olive farms of 10 ha or less in the region of Chebika is 1270 farms (CRDA, 2014). These farms are mainly concentrated in three small villages. From this population of 1270 farms, a random sample of 250 was extracted. Finally, the 250 owners/renters of the selected olive farms were contacted by the two representatives of the CRDA, and 75 gave their consent to participate in the survey. The questionnaire was administered during the month of March 2017, in face-to-face mode, since an important proportion of the respondents are illiterate. Finally, 70 farmers participated to the survey, resulting in a response rate of 28% (70/250). Even though the size of our sample is somewhat low, it still acceptable. comparable or higher than many previous studies on the assessment of efficiency in various agricultural activities. As showed by the meta-analysis of farm efficiency conducted by Bravo-Ureta et al. (2017), numerous studies exhibited a number of observation comparable or lower than ours (e.g., D'Haese et al. (2009)-Dairy production in France: 34 Obs.; Khoshnevisan et al. (2013)-Wheat in Iran: 26 Obs.). It is worth noting that before launching the survey, we obtained a certificate of ethics approval from the ethics committees for research involving humans at our university of affiliation.

### 3.4 Empirical Specification

In this study, we assess the technical efficiency of Tunisian olive producers and we identify the factors which may influence this efficiency, respectively, by using the DEA and fsQCA.

*The DEA Analysis*

In this study, the DEA method is used to measure the efficiency across our sample of Tunisian olive producers. This non-parametric approach (Banker et al., 1984; Charnes et al., 1978) was widely used to assess the efficiency of decision-making units (DMUs) in several settings and contexts (e.g., Sefeedpari et al., 2020: Dairy farming; Amara et al., 2020: Higher education institutions). Among the advantages that the DEA method provides in comparison with others is that it does not impose a functional form on the production frontier and hence can accommodate wide-ranging behaviors. This is of great importance when the usual axioms of profit maximization break down. This might be the case of some of the units of production composing our sample due to their very small size and to the differences in farmers' management styles. Moreover, the DEA is less restrictive than parametric approaches regarding the types of data and information requirements. Broadly speaking, the DEA approach defines a DMU's "technical efficiency" as each DMU's relative ability to maximize its efficiency ratio (output over input) by choosing the best set of weights (Amara et al., 2020). The DEA approach includes two variants: 1) input-oriented: the ability to minimize input when the output is given; and 2) output-oriented: the maximization of output given a certain bundle of inputs (Charnes et al., 1978). This study adopts an output-oriented DEA perspective. As contended in many previous studies, the typical problem in small units of production—such as the olive farms composing our



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sample—does not involve minimizing inputs while maintaining the same level of outputs. Rather, they will try maximizing outputs, given the bundle of inputs involved in the production cycle. Finally, this study uses the variable returns-to scale (VRS) over the constant returns-to-scale model (CRS). The VRS model is more appropriate for our study than the CRS model because, as our sample is heterogeneous, it compares each DMU only with those DMUs of comparable size (Zarrin & Brunner, 2023).

*The Determinants of Olive Farmers' Efficiency: Symmetric and Asymmetric Analyses*

According to numerous researchers from different research fields (Rasoolimanesh et al., 2021; Woodside, 2013), symmetric approaches as regressions paints an incomplete picture regarding the impact of a set of predictors on the phenomena under study because they quantify the average impact of every single explanatory variable. On this matter, Rasoolimanesh et al. (2021, p. 1572) contended that "*to address this concern, researchers have called for the use of asymmetric approaches that process and analyze each individual case instead of the variables*". Such asymmetric approaches explore how various combinations of conditions (i.e., independent variables) generate outcome for different groups of cases. Consequently, the combination of symmetric and asymmetric approaches is increasingly encouraged by many authors (Rasoolimanesh et al., 2021) advocating that it can provide more robust findings and better actionable recommendations for practitioners. As part of this trend, this study combined symmetric techniques (OLS and Tobit regressions) with an asymmetric technique (Fuzzy-set qualitative comparative Analysis (fsQCA)) to identify the main antecedents that might explain the gaps in efficiency among small Tunisian olive farmers.

- Symmetric Analyses: OLS and Tobit Regressions

The DEA method enables to calculate the individual efficiency scores of the olive farms composing the sample under study. To identify the factors that potentially explain the variations in the efficiency scores among the olive farms, these scores are considered as a dependent variable in an auxiliary regression, and regressed on the five previously introduced independent variables: farmer's level of education, access to agricultural credit, off-farm income, ownership status of the land, and farmer's age. Regarding the appropriate regression type to use, this study estimated both an OLS and a Tobit regressions. This is to reconcile the strand of researchers advocating that the efficiency scores from a censored dependent variable (values ranging between zero and one) should be estimated with a Tobit regression (Cecchini et al., 2023), with researchers contending that the OLS regression is more appropriate when the efficiency's score is drawn from the estimation of a non-parametric frontier (as is the case in this study) (Amara et al., 2020). Indeed, for the tenants of the first strand, the efficiency scores from a censored dependent variable (values ranging between zero and one) should be estimated with a Tobit regression (Cecchini et al., 2023). On this matter, Fitzová et al. (2018) mention that when we intend to explain the obtained efficiency DEA scores, Tobit regression is the common model to estimate « *as efficiency scores are bounded by zero from below and by one from above with a positive probability to take on the value at the end of the interval.* » (Fitzová et al., 2018, p. 4). In contrast, the tenants of the second strand contend that the OLS regression is more appropriate when the efficiency's scores are drawn from the estimation of a non-parametric frontier (as is the case in this study) (Amara et al., 2020).

- Asymmetric Analysis: The Fuzzy-Set Qualitative Comparative Analysis (fsQCA)



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fsQCA is a configurational research technique that aims to investigate the combined impact that key explanatory conditions have on an outcome across a set of cases (Ragin, 2008). While regression assessed the isolate impact of an independent variable on a dependent variable, fsQCA is built on a set theory to identify necessary and sufficient configurations of conditions that enable achieving a given outcome (Eng & Woodside, 2012). It considers that outcomes of interest seldom have a single cause (multi-causality). These causes are always interdependent, and a specific cause may have either positive or negative effects depending on context (asymmetry). Moreover, fsQCA is particularly useful for examining equifinality. Equifinal solutions, that could be viewed as alternative pathways to achieve an outcome of interest, provide insightful information for managers because they offer them a variety of optional choices to attain the desired outcome by following the pathway that better fits with their features, available resources, and strategic orientation (Payne, 2006). Additionally, and contrary to conventional statistical methods that often discard extreme responses, fsQCA considers these “data outliers” are highly informative on the studied phenomenon (Eng & Woodside, 2012). To identify the combinations of antecedents leading to the outcome of interest, fsQCA relies on Boolean algebra rather than linear arithmetic. It builds upon the premise that relationships among different conditions are better apprehended in terms of set membership. As contended by Ragin (2008), a set membership score is not restricted to dichotomous values (1 and 0), but could range from ordinal up to continuous values. Thus, a fuzzy set can be viewed as “a continuous variable that has been purposefully calibrated to indicate the degree of membership in a well-defined and specified set” (Ragin, 2008, p. 30). The fsQCA analysis involves the calculation of calibration values for continuous variables (outcome and conditions) and the analysis of the five conditions, namely farmer’s level of education, access to agricultural credit, off-farm income, ownership status of the land, and farmer’s age, on the outcome of interest: efficiency of Tunisian olive producers. The selection of threshold values for calibration depends on both theory and the researcher’s knowledge of the cases under analysis. For the two continuous variables in our model, namely efficiency scores and farmer’s age, decisions about full membership and non-membership will involve assessing what levels of efficiency and age are generally considered high versus low. This study calibrated the outcome’s values (the efficiency scores obtained using the DEA approach) and the condition referring to farmer’s age according to the following three thresholds: 10%, or low agreement or fully outside the set; 50%, or an intermediate level of agreement that is neither inside nor outside the set; and 90%, or high agreement or fully inside the set. Many prior studies have used these thresholds to calibrate original variables’ values (Amara et al., 2020; Woodside, 2013). For the other four conditions measured with dichotomous variables, a value of one indicates that a farmer is fully inside the set (high agreement), whilst a value of zero indicates that the farmer is fully outside the set (low agreement). After the calculation of calibration values, the fuzzy-set membership scores are transformed into a truth table that reports all logically possible combinations of causal conditions and each configuration's empirical outcome (Eng & Woodside, 2012). Thereafter, necessary and sufficient condition tests were performed to evaluate the different conditions’ combined effects on an olive producer’s efficiency and on the absence of an olive producer’s efficiency. A causal condition is defined as necessary if it must be present for an outcome to occur, and as sufficient if, by itself, it can produce a certain outcome (Ragin, 2008). Thus, we assume that the presence of the five conditions should lead to the outcome (olive producer’s efficiency). The fsQCA enables to obtain three types of solutions: a complex, a parsimonious, and an intermediate solution. Each of these solutions provides configurations of causal conditions conducive to the outcome of interest. The parsimonious and conservative solutions are the two extremes of a continuum: the conservative solution makes no assumptions, but can be hard to interpret, while the parsimonious solution is easier to interpret, but necessitates many assumptions that can be untenable or contrary to previous theoretical predictions. The intermediate solution removes the untenable assumptions and considers the theory-driven counterfactuals**.** It is considered



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as a superset of the conservative solution, and a subset of the parsimonious solution. In this study, the intermediate solution generated by fsQCA is considered and an analysis was performed thanks to fsQCA software, version 2.5.

## 4. RESULTS AND DISCUSSION

This section presents the results of the empirical exercise, respectively, for the DEA assessment of Tunisian olive producers' efficiency, and for OLS, Tobit, and fsQCA models.

### 4.1 Assessment of Tunisian Olive Producers' Efficiency Using DEA

We estimated an output-oriented VRS efficiency model that considers one output (quantity in kilograms of olives obtained during the 2017 campaign), and three inputs, namely the area in hectares of land devoted to olives, the amount of labor expressed in man-total number of working days per campaign (permanent and occasional salaried workforce, as well as familial workforce), and the quantity in kilograms of mineral and organic fertilizers used in olive production during the 2017 campaign. The software Deap version 2.1 was used to obtain DEA efficiency scores for the seventy Tunisian olive producers belonging to our sample. Results reported in Table 1 testify that there is high inefficiency across the sample, which indicates that substantial room for improvement exists in the efficiency among Tunisian olive producers. This means that they could significantly improve their olive production while maintaining the same bundles of inputs. Overall, the mean efficiency score is 56.50% (Median= 60.88%), and these scores range in value from 12.78% to 100%. Almost a third of the farmers did not reach 50% efficiency, and more than 9 farmers out of 10 did not reach 75% efficiency.

Tab. 1 – DEA scores of technical efficiency among Tunisian olive farms

| Statistics | Minimum | Maximum | Median | Mean | Standard Deviation |
|---|---|---|---|---|---|
| | 12.78 | 100.00 | 60.88 | 56.50 | 14.94 |

| | Number | % |
|---|---|---|
| Less than 25% of efficiency | 3 | 4.3 |
| 25% to 49.99% of efficiency | 19 | 27.1 |
| 50% to 74.99% of efficiency | 43 | 61.4 |
| 75% to 100% of efficiency | 5 | 7.2 |
| | **70** | **100%** |

### 4.2 Regressions Results Regarding the Determinants of Tunisian Olive Producers' Efficiency

Panels A and B in Table 2 report the results of the estimations from the OLS and the Tobit explanatory models of Tunisian olive farms' efficiency. The two models are significant at the 1% level, as indicated by the values of the calculated F for the OLS regression and Wald's statistic for the Tobit regression; these are both greater than their critical values (4.01 versus 3.32 and 18.42 versus 15.09,



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respectively). Regarding the explanatory variables, the two models revealed that the four same variables are significantly associated with higher olive farms' efficiency scores, namely farmer's level of education (EDUC), access to agricultural credit (CRED), farmer's age (AGE), and off-farm income (OINCOME). The first three variables are positively associated with higher efficiency scores, whilst the fourth variable is negatively associated with higher efficiency scores. These results are in line with the findings of many previous studies. Indeed, regarding farmer's level of education, many studies showed that higher-educated farmers are more efficient than less educated ones (Giannakas et al., 2000; Lachaal et al., 2005; Lambarraa et al., 2007). This is because educated farmers are more able to integrate new agricultural practices in their farming activities and are more likely to adopt new and more productive technologies (Rodrigues et al., 2023). Likewise, access to agricultural credit was found positively associated with farms efficiency in several previous studies. For instance, authors as Rodrigues et al. (2023) contended that the availability of financial resources might offer the small farmer the opportunity to undertake productive investment that are not able to undertake otherwise (procurement of modern inputs, hiring of additional employees, adoption of productive technologies, etc.). Regarding farmer's age, our findings corroborate those of the strand of studies advocating that older farmers are more likely to have a cumulative farming experience allowing them to have better farm-level decision-making, more adequate equipment and machines, better networks of clients and suppliers, and better access to labour than the younger farmers (Giannakas et al., 2000; Lambarraa et al., 2007). Finally, our findings regarding the impact of off-farm income on efficiency are in line with the strand of studies contending that the farmers' involvement in off-farm activities might affect a negatively their efficiency level as it could be detrimental to the course of agricultural schedule and the right timing of agricultural activities. It also may lead to less informed managerial decisions, and a misallocation of resources (Harmini et al., 2022).

Tab. 2 – Estimated linear and Tobit regression models of factors affecting Tunisian olive farms' technical efficiency scores

| | Dependent Variable: Olive Farms' Efficiency Scores [*EFFIC*] | | | |
|---|---|---|---|---|
| | *PANEL A: Linear regression (OLS)* | | *PANEL B: Tobit regression* | |
| **Independent variables** | *Coeff. (β)* | *P-value* | *Coeff. (β)* | *P-value* |
| Intercept | 13.040 | 0.616 | 43.551 | 0.000 |
| • Farmer's Level of education [*EDUC*] | 6.679** | 0.024 | 6.594** | 0.027 |
| • Access to agricultural credit [*CRED*] | 10.597*** | 0.006 | 10.529*** | 0.004 |
| • Farmer's age [*LNAGE*][a] | 10.319** | 0.036 | 0.193* | 0.061 |
| • Off-farm income [*OINCOME*] | -6.178** | 0.041 | -6.241** | 0.038 |
| • Ownership status of the land [*STATUS*] | 0.010 | 0.499 | -0.171 | 0.487 |
| Number of cases | 70 | | 70 | |
| Adjusted R-squared: | 0.276 | | --- | |
| McFadden's Pseudo R-squared | --- | | 0.182 | |
| Calculated *F*: [Theoretical *F* (*5*; *63*) = 3.32 at 1%] | 4.01*** | | --- | |
| Log likelihood | --- | | -277.20 | |



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| | | |
|---|---|---|
| Wald-statistic [Theoretical Chi-square (5) = 15.09 à 1 %]: | --- | 18.42*** |

****** and ******* indicate that the variable is significant at the 5% and 1% levels, respectively.
[a] LN indicates a logarithmic transformation.

### 4.3 fsQCA Results Regarding the Antecedents of Tunisian Olive Producers' Efficiency

Table 3 displays the descriptive statistics for the continuous variables as well as the calibration values used to convert the variables into fuzzy-set conditions. An overview of the detailed operationalization and descriptive statistics of the input, output, and factors that may affect olive farmers' efficiency is provided in appendix A.

*Analysis of Necessary Conditions*

To assess whether any of the five antecedents' conditions are necessary for the olive farmers to achieve efficiency, the study tests whether the condition is always present (or absent) in all cases where the outcome is present (or absent). This is indicated by the consistency scores. A condition is "necessary" when its consistency score exceeds the threshold of 0.9 (Ragin, 2008). Table 4 presents the results of the fsQCA test on the necessity of the conditions relative to the outcome (efficiency of olive farmers). We can see that none of the five conditions is a necessary condition of the outcome's occurrence, nor of its non-occurrence, as indicated by the consistency values that are all under 0.90.

Tab. 3 – Descriptive statistics and calibration values of outcomes and conditions[a]

| | Olive production Efficiency [*EFFIC*] | Farmer's age [*AGE*] |
|---|---|---|
| *N* | 70 | 70 |
| *Missing data* | 0 | 0 |
| *Mean* | 56.50 | 50.83 |
| *Median* | 60.88 | 51.50 |
| *Standard deviation* | 14.94 | 14.24 |
| *Minimum* | 12.78 | 28 |
| *Maximum* | 100 | 84 |
| *Calibration values* | | |
| 10th percentile | 34.36 | 30.20 |
| Median (50th) | 60.88 | 51.50 |
| 90th percentile | 73.45 | 70.00 |

[a] NOTE: Four binary variables—Level of education [*EDUC*], Access to agricultural credit [*CRED*], Off-farm income *[OINCOME]* and Ownership status of the land [*STATUS*]—are also considered as conditions for the occurrence/non-occurrence of the outcome.



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Tab. 4 – Necessary conditions for the occurrence (and non-occurrence) of olive production efficiency

| | *EFFIC* | | *~EFFIC* | |
|---|---|---|---|---|
| | Consistency | Coverage | Consistency | Coverage |
| *AGE* | **0.671858** | **0.660600** | 0.601242 | 0.600085 |
| *~AGE* | 0.593270 | 0.594433 | **0.659945** | **0.671214** |
| *EDUC* | 0.528211 | **0.655321** | 0.273694 | 0.344679 |
| *~ EDUC* | 0.471789 | 0.390214 | **0.726306** | 0.609786 |
| *CRED* | 0.309432 | **0.671812** | 0.148914 | 0.328187 |
| *~ CRED* | **0.690569** | 0.444241 | **0.721086** | 0.555759 |
| *OINCOME* | 0.191981 | 0.333450 | 0.378056 | **0.666550** |
| *~ OINCOME* | **0.788020** | 0.561380 | 0.621944 | 0.438620 |
| *STATUS* | **0.723913** | 0.489645 | **0.753340** | 0.510355 |
| *~ STATUS* | 0.226087 | 0.547500 | 0.132660 | 0.452500 |

Note: *in bold = highest conditions but not necessary (less than 0.90); *AGE*: Farmer's age; *EDUC*: Level of education (Primary level or more/illiterate); *CRED*: Access to agricultural credit (Yes/No); *OINCOME*: Farmer's off-farm income (Yes/No); *Status*: *Ownership status of the land (Owner/Renter)*.

*Analysis of Sufficient Conditions*

A threshold of 0.78 was established based on a break in the distribution of consistency scores to determine sufficient conditions (Ragin, 2008). We draw on an intermediate solution from the truth table to determine whether a given condition or combination of conditions would be conducive to the presence of olive farmers' efficiency. The results of the intermediate solution presented in Table 5 indicate four paths of causal conditions that can explain Tunisian olive farmers' efficiency. Following the recommendation by Eng & Woodside (2012) in that a model is predictive of high scores for an outcome if consistency and coverage thresholds are greater than 0.80 and 0.10, respectively, we conclude that our model's overall consistency and overall coverage values are satisfactory (0.82495 and 0.49447, respectively). This means that the four causal configurations explain 49.45% of the empirical cases. Moreover, the four sufficient conditions' raw coverage values range between 0.248 and 0.404, which is also considered satisfactory (Eng & Woodside, 2012).

We follow the notations used by Pappas & Woodside (2021) to present, in a more intuitive way, the solutions obtained from fsQCA. More specifically, the presence of a condition is indicated with a black circle (●), the absence/negation with a crossed-out circle (⊗), and the "do not care" condition with a blank space. The distinction between core and peripheral conditions is made by using large and small circles, respectively. The core conditions, suggesting a strong causal relationship with the outcome, appear in both parsimonious and intermediate solutions, while peripheral conditions, suggesting a low causal relationship with the outcome, appear only in the intermediate solution (Pappas & Woodside, 2021).

The first configuration represents younger farmers that are renters of the lands they operate, but who have off-farm income and access to agricultural credit. These results suggest that to be efficient, younger farmers who are not the owners of the lands they operate must generate off-farm income and raise agricultural credit. For this group of farmers, this latter condition seems to have a strong causal



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relationship with their level of efficiency (present core condition). The particular importance of access to agricultural credit revealed in this configuration is aligned with the findings of a dominant stream of studies that have identified positive causal effect between access to agricultural credit and efficiency. In this vein many authors argued that the availability of financial resources is crucial to better fulfill the production objectives, such as investment in farm infrastructure, procurement of modern inputs, finance of additional work labour, adoption of productive technologies, and reduction of risks and unforeseen expenditures (Rodrigues et al., 2023).

The second configuration represents the younger farmers who generate off-farm income, are not illiterate (have primary education level or more) and are the owners of the lands they operate. The two last conditions are core ones. Thus, this group of farmers becomes efficient by compensating for their lack of experience (younger farmers) with their level of education, their favorable ownership status (owners of the land they operate), and their capacity to generate income from other sources than the olive production. The lack of farmer's experience seems then very detrimental to efficiency to the point that several other conditions should prevail to counter its negative effect on efficiency. This result is consistent with the findings of numerous prior studies revealing that more experienced farmers (as measured by their age) are more likely to have a cumulative farming experience enabling them to have better farm-level decision-making, more adequate equipment and machines, better networks of clients and suppliers, and better access to labour than the younger farmers (Paul, 2023).

The third configuration refers to the group of farmers who are older, owners of the lands they operate, are not illiterate, and unable to generate off-farm income. The first condition is peripheral, while the following three are core ones. Thus, this group of farmers compensates for their inability to yield income from other sources than olive production with their level of education, their experience (older farmers), and their status of owners of the lands they operate to produce olives. It worth noting that the absence of off-farm income is a core causal condition in this configuration. This might suggest that this group of farmers are totally dedicated to olive production and are reluctant to engage in off-farm work. This is in line with the results of other studies, such as those by Harmini et al. (2022), which found that the off-farm work is generally done at the expense of the time normally devoted to farming activities. Finally, the fourth configuration reflects a group of less experienced farmers (younger) who are not able to generate off-farm income but are not illiterate and have access to agricultural credit. This latter condition seems to have a strong causal relationship with their level of efficiency (present core condition). More specifically, this fourth configuration shows that education and access to agricultural credit compensate for farmers' lack of experience and their inability or their unwillingness to generate off-farm income. As for the first configuration, the access to agricultural credit is exhibited as a core condition, which testifies of its great importance, particularly for the more educated young farmers to better fulfill their production and performance goals (Rodrigues et al., 2023).



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Tab. 5 – Sufficient conditions (intermediate solution) for olive production efficiency

| *Frequency Cutoff: 1* | Research Efficiency *[Consistency cutoff: 0.787863* | | | |
|---|---|---|---|---|
| | **1** | **2** | ***3*** | ***4*** |
| Farmer's Level of education [*EDUC*] | | ● | ● | • |
| Access to agricultural credit [*CRED*] | ● | | | ● |
| Off-farm income [*OINCOME*] | • | • | ⨂ | ⊗ |
| Ownership status of the land [*STATUS*] | ⊗ | ● | ● | |
| Farmer's age [*AGE*] | ⊗ | ⊗ | • | ⊗ |
| Consistency | 0.840100 | 0.811020 | 0.795671 | 0.712640 |
| Raw coverage | 0.317629 | 0.248362 | 0.264552 | 0.404566 |
| Unique coverage | 0.131556 | 0.025332 | 0.031508 | 0.231778 |
| ***Overall solution consistency:*** | 0.82495 | | | |
| ***Overall solution coverage:*** | 0.49447 | | | |

Note*:* ● = core casual condition (present), • = peripheral casual condition (present), ⨂= core casual condition (absent), ⊗ = peripheral casual condition (absent). Blank space indicates "do not care about this condition" (absence or presence is not important in that particular configuration in regard to the outcome; all sufficient conditions have adequate raw coverage (between 0.248 and 0.404). Expected vector for Research Efficiency: 1.1.1.1.1 (0 is absent; 1 is present).

## 5 CONCLUSION

The findings of this study carry important implications for farmers, central and regional government agencies promoting and supporting agriculture, and policy-makers. First, the results of both regressions and fsQCA show that the level of education matters in improving olive farmers' efficiency. As 60% of the farmers surveyed are illiterate (see appendix A), it is of great importance to promote basic education in order to be more receptive to new production technologies and good agricultural practices. This can be done by implementing a literacy program targeting illiterate farmers. Such a program will thereafter facilitate the farmers' access to professional and specialized agricultural training, particularly in production techniques and good agricultural practices (such as harvesting techniques and pruning, techniques for optimal use of fertilizers, adequate irrigation methods, cropping calendar requirements, etc.). Extension activities and awareness sessions for farmers, led by regional agricultural development actors, should be very beneficial in this matter. Second, the findings of this study also show that the access to agricultural credit plays a significant role in enhancing farmers' level of efficiency. This is more important as these farmers do not have the financial means to acquire the necessary assets and cannot afford to invest in olive growing. Therefore, the areas of improvement, identified in the previous point regarding farmers' education and training, should be accompanied by a favorable institutional environment promoting microcredits and insurance programs for the benefit of farmers to facilitate their accessibility to productive resources,



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such as fertilizers, plantations, and small agricultural equipment. This can be done by facilitating these small olive growers' access to financial services to increase their chances of obtaining seasonal credits, with subsidized interest rates and more flexible guarantee procedures, both from public and private sectors. Third, the results also highlighted the importance of the status of land ownership on the farmers' efficiency. We found that the farmers owning the land they operate are more likely to achieve higher levels of efficiency than those who are renters. However, there is a serious land tenure security issue for the owners because the majority of them do not have land titles for the agricultural holdings they operate. The absence of such land titles leads to difficulties in accessing credit in rural areas. Therefore, it is crucial to assign land titles to owners that can serve as collateral for credit providers. Finally, there is an urgent need for legislative intervention to control and limit the phenomenon of land fragmentation, due notably to an inheritance. Farmers operating smaller and smaller farms will certainly not be able to integrate the best cultural practices, adopt technological innovations, fully invest in olive production, access credit, etc., and thus achieve high levels of productivity and efficiency.

This study has some limitations that future research should endeavor to overcome. First, although it involves the exploitation of an original dataset and powerful analytical tools, it is still exploratory, in that it is among the first to investigate the technical efficiency of small olive producers in a developing country. Thus, the results should be interpreted with caution. Second, this study relies on self-reported data. Such data may include some biases related to social desirability. Despite these limitations, this study's results enhance our understanding of the extent and determinants of olive farmers' efficiency operating small farms in a developing country, but one of the most important olive producers in the world. It also enriches the body of literature regarding the assessment of efficiency by combining, in an original way, two analytical techniques drawing on two different logic foundations (regressions and Fuzzy-set Qualitative Comparative Analysis). Nevertheless, further research is required to deepen our understanding of the issues surrounding olive production in small rural farms. For instance, in this study, olive growing was considered as a monoculture system. However, olive farms in rural areas produce other outputs at the same time (poultry, livestock, market gardening, etc.), albeit in smaller quantities than olives. Decision-making therefore concerns the overall management of the farm. Further research is needed to address the multi-output situation of olive farms to better understand the effects of the olive-growing system on other agricultural productions. Regarding the estimation of efficiency scores, it would be interesting to compare the two approaches, parametric and non-parametric, to better validate the results. Finally, to enrich the analysis, future research may measure the allocative efficiency of olive farms (by taking input prices into account), and thus address the question of their overall performance (technical and allocative efficiencies).

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Append. A – Definitions and descriptive statistics of output, input, and the determinants of olive farmers' efficiency

| Measure | Sub-Items | Mean (SD) | % (Number) |
|---|---|---|---|
| OUTPUT: | | | |
| *Olive production* [OLIVE] | • It is expressed in kilograms of olives obtained during the 2017 campaign. production. | 25088 (23763) | |
| INPUT: | | | |
| *Agricultural area* [AREA] | • The area in hectares of land devoted to olive production | 5.00 (2.42) | |
| *Workforce* [WORK] | • The amount of labor used by the operator. It is expressed in man-total number of working days per campaign and represents the sum of the labor used to carry out all the cultivation operations. It encompasses the permanent and occasional salaried workforce, as well as familial workforce. | 42.20 (15.28) | |
| *Fertilizers* [FERTL] | • Measured in kilograms and corresponds to the use of mineral and organic fertilizers in olive production for the 2017 campaign. | 251.99 (385.49) | |
| FACTORS AFFECTING OLIVE PRODUCTION EFFICIENCY: | | | |
| *Age* [AGE] | Measured as the number of years between 2017 and the year of birth of the farmer. | 50.83 (14.24) | |
| *Level of education* [EDUC] | Dichotomous variable:<br>- Coded as one if the farmer has a primary education level or more, and zero otherwise (he is illiterate):<br>• *Primary level or more*<br>• *Illiterate* | | 40.0% (28)<br>60.0%% (42) |
| *Access to agricultural credit* [*CRED*] | Dichotomous variable:<br>- Coded as one if the farmer had access to agricultural credit during the last three years preceding the survey, and zero otherwise:<br>• *Access to agricultural credit*<br>• *No access to agricultural credit* | | 22.9% (16)<br>77.1% (54) |
| *Off-farm income* [OINCOME] | Dichotomous variable:<br>- Coded as one if the farmer generates non-agricultural income (e.g., independent activities, formal and informal salaried income), and zero otherwise:<br>• *Off-farm income*<br>• *No off-farm income* | | 28.6% (20)<br>71.4% (50) |
| *Ownership status of the land* [STATUS] | Dichotomous variable:<br>- Coded as one if the farmer is the owner of the land, and zero if he is the renter of the land:<br>• *Owner*<br>• *Renter* | | 88.6% (62)<br>11.4% (8) |



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