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Competitiveness and resilience dynamics in the Italian olive sector: An in-depth analysis

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Abstract

This paper investigates the interaction among potential and revealed resilience capacities, technical efficiency, and total factor productivity (TFP) in Italian olive farms using FADN data from 2013-2019. To achieve this objective, we use principal component analysis for evaluating potential resilience indicators and a stochastic frontier model (SFM) to assess farms' competitiveness and evaluate the impact of resilience measures on farms' efficiency and productivity. Results show that Italian olive farms exhibit higher resilience in transformability, followed by robustness and adaptability. Resilience indicators negatively impact technical efficiency. TFP growth is notably influenced by adaptability. Results suggest that balancing competitiveness and resilience is crucial to achieving a sustainable farming system. To face climate change challenges, policies should facilitate transitions to a climate-resilient farming system by incentivizing investments in climate-adaptive technologies and designing careful subsidy programs that emphasize the long-term resilience benefits of sustainable farming practices rather than considering immediate efficiency gains. Farmer support through training and collaborative networks is vital to strengthening farms' adaptability and transformability capacities.

JEL Codes: C190, D290, C010



I. INTRODUCTION

Italy stands as one of the leading producers of olives and olive oil within the European Union, making a substantial contribution to the country's overall agricultural output. The olive sector's significance extends beyond economic relevance, encompassing social and environmental dimensions. Several factors justify the relevance of the olive sector in Italy. Firstly, olive cultivation holds a pivotal role in the EU agricultural model across the Mediterranean region since out of the 4.6 million hectares of EU land designated as olive groves, Italian ones account for 23% (Eurostat dataset, 2017). Secondly, the majority of olive production occurs in less developed regions, falling under the Objective 1 category of the EU regional policy. This concentration makes these regions crucial sources of employment and economic activity. Thirdly, Italy accounts for the largest share of protected olive oil labels, comprising approximately 40% of the EU Protected Designations of Origin (PDOs) and Protected Geographical Indications (PGIs) (Belletti et al., 2015). Lastly, under the new Common Agricultural Policy (CAP), Italian agriculture is set to receive subsidies totaling 34 billion from 2023 to 2027, with 25% of direct payments explicitly allocated for farmers engaged in environmental practices to conserve biodiversity.

Despite its significance and supportive EU policies, the Italian olive sector faces challenges leading to a decline in yields over the years. Factors contributing to this decline include traditional practices, limited technological innovation, landscape protection measures, and unsustainable agricultural systems. Climate change effects, such as pest attacks, extreme weather conditions aggravate these challenges (ISMEA, 2021, Rezgui et al, 2024).

On the other side, despite the widespread presence of olive cultivation across the Italian peninsula, the production of olives suffers from fragmentation, with the average olive grove covering only 1.8 hectares of land. Competitiveness is a major issue for the Italian olive sector due to production and market fragmentation, diverse cost dynamics, an aging farmer population, and a significant labor shortage. Many olive groves house old, inefficient trees, impacting profitability. In 2022/2023, Italy produced 235 thousand tons of oil, a significant decrease from the 329 thousand tons in 2021/2022 (DeAndreis, 2023, Rosati et al, 2013).

Addressing these challenges necessitates an in-depth analysis of the competitiveness and resilience of the olive sector. This paper aims to address the research gap by analyzing the dynamics and trade-offs between resilience capacities, total factor productivity, and technical efficiency in the Italian olive sector. Understanding the interaction of resilience indicators with total factor productivity over the years will provide insights into improving yields during alternate bearing years of olive farms. As specific objectives, the aim is to assess the potential and revealed resilience indicators of Italian olive farms, analyze the impact of potential resilience capacities on the technical efficiency, assess the Total Factor Productivity (TFP) of

Italian olive farms, and understand the synergies between revealed resilience, TFP, and the potential resilience of Italian olive farms.

In assessing farm resilience, it is crucial to examine both potential and revealed resilience. Potential resilience encompasses three critical capacities—robustness, adaptability, and transformability—while revealed resilience is revealed through efficiency changes. These concepts converge in the sphere of total factor productivity. Recent studies indicate that technological advancements play a pivotal role in fostering resilience (Zawalińska et al., 2022). Resilience, in this context, denotes a system's ability to withstand adverse shocks, recover, and sustain its fundamental structure and functions. Resilient farming practices not only contribute to TFP growth by facilitating technological and efficiency changes but also exert influence on ecosystem services and natural capital through externalities and feedback mechanisms. Our study focuses on exploring of how resilience is manifested in TFP changes and its subsequent decomposition. By differentiating between potential resilience, represented, and revealed resilience, illustrated in TFP changes, we aim to shed light on the synergies between farm resilience and total factor productivity.

II. METHODOLOGY FRAMEWORK

To examines the interaction among potential and revealed resilience capacities, technical efficiency, and TFP in Italian olive farms using FADN farm resilience is divided into potential resilience—assessed through capacities like robustness, adaptability, and transformability—and revealed resilience, measured by observable responses to shocks through changes in TFP. The SFM is employed to measure competitiveness and assess the impact of resilience on efficiency. TFP is then decomposed to observe revealed resilience (Figure 1)

II.1. Potential and revealed resilience

Following Zawalińska et al. (2022), farm resilience comprises potential and revealed aspects. Potential resilience is assessed through resilience capacities including farm robustness, transformation, and adaptability. While revealed resilience is demonstrated through observable responses to the ex-post the shocks by observing the changes in the Total Factor Productivity.



Source: Authors

Figure 1. Methodological approach

a. Potential resilience

Potential resilience is defined as the farm's ability to fulfill its functions in the face of economic, environmental, institutional, and social shocks through resilience capacities: robustness, adaptability, and transformability (Meuwissen et al., 2019). These capacities empower the farm to withstand (robustness) and recover from and respond (adaptability and transformation) to stresses (Gaviglio et al., 2021).

Robustness is defined as the capacity to withstand, absorb, and recover from both expected and unexpected shocks. To quantify robustness, three indicators are utilized: resistance, shock, and recovery rate. Each of the three is based on farm profitability. Resistance pertains to the level of profitability decrease, with a shock identified when profitability experiences a drop of at least 30%. The recovery rate reflects the extent to which the system rebounds after a decline in profitability. The rate of return on Assets (ROA) is considered an indicator of profitability (Barry and Ellinger, 2011).

Resistance is described as the farm's ability to absorb the consequences of risks by minimizing decreases in farm income or profitability (Urruty, Tailliez-Lefebvre, and Huyghe, 2016). Therefore, we define resistance as the decrease in profitability of farms over time. Resistance is a continuous variable within the domain of (0, -1), where 0 indicates the most resistant farms and -1 indicates the least resistant farms.

$$resistance_t = \begin{cases} \frac{ROA_t - ROA_{t-1}}{ROA_{t-1}} & 0 \\ & if ROA \geq ROA_{t-1} \\ & if ROA < ROA_{t-1} \end{cases} \quad (1)$$

Shock is defined as the ability of a farm to withstand successive risks (Sabatier et al., 2015; Sneessens et al., 2019). A severe shock, therefore, is defined as a decrease in normalized profitability by at

least 30%. If the value lies below 30%, it is recorded as 1, indicating a severe shock, and 0 if no shock occurred.

$$shock_t = \begin{cases} 0, & resistance_t < -0.3 \\ 1, & resistance_t \geq -0.3 \end{cases} \quad (2)$$

Recovery rate describes the degree of recovery after a set amount of time, given that the normalized profitability has decreased (Urruty, Tailliez-Lefebvre, and Huyghe, 2016; Sneessens et al., 2019; Dardonville, Bockstaller, and Therond, 2021). It is a measure of the degree to which a farm can bounce back. A lower recovery rate indicates a poor ability of a farm to bounce back after a shock. On the contrary, a higher recovery rate indicates better recovery after a shock. Its values lie within the domain (0, 1), where 0 indicates no recovery and 1 indicates full recovery.

$$Recovery\ rate_{-}(t+1) = \begin{cases} 1 & if \quad ROA_t \geq ROA_{t-1} \\ \frac{ROA_{t+1}-ROA_t}{ROA_{t-1}-ROA_t} & if \quad ROA_t < ROA_{t-1} \end{cases} \quad (3)$$

Adaptability is reflected by changes in a farm's input composition, production, marketing, and risk management. Adaptability is therefore either an increase or decrease in input composition and production processes. Adaption consists of the following four indicators: crop diversity, specific costs which is a summation of changes in fertilizers, water, seed protection, insurance, greenhouse materials, certifications, and external services. The last two indicators are irrigated area and total labor hours. The direction of each adaptability indicator is not interpretable in favor of more or less intensification in farming systems, as intensification can have a positive or negative impact on the adaptability indicator. Therefore, to avoid making normative statements about the desired direction of adaptability, this paper only uses absolute values for the adaptability indicators, as discussed by Slijper et al. (2022).

Crop diversity is measured using the Shannon Diversity Index (SDI). It is defined as reflecting the evenness (the proportion of land covered by a crop) and richness (the number of different crops) of a crop portfolio (Brady et al., 2009).

$$SDI_{it} = - \sum_{c=1}^C p_{cit} \ln(p_{cit}) \quad (4)$$

Where SDI (Shannon Diversity Index) represents the diversity of crops at a specific time t. The variable p_{cit} denotes the proportion of land occupied by crop i (where i can be cereals, other field crops, vegetables and flowers, vineyards, permanent crops, other permanent crops, forage crops, or woodland) during that time t. The change in crop diversity is indicated by the yearly change in SDI (Smit and Skinner, 2002; Kremen and Miles, 2012). Changes in the intensity of the production process of a farm are a measure of adaptation. In this paper, we use changes in specific costs, which are a summation of changes in fertilizers, water, seed protection, insurance, greenhouse materials, certifications, and external services, as a measure of adaptation. Irrigation, the third indicator, serves as an adaptive strategy for regulating water availability, particularly in addressing droughts and unfavorable weather circumstances (Howden et al., 2007). Ultimately, changing the labor intensity per hectare represents an adaptive approach that showcases a farm's capacity to adapt to high-demand periods.

Transformability is defined as the fundamental and integral changes in the internal farm structure to cope with risks. Transformation capacity consists of three indicators: organic farming, farm tourism, and change of farm type. Organic farming refers to the ability of the farm to transform from conventional to organic or vice versa. Utilized agriculture area (UAA) represents the change in farm type and its outputs. Finally, obtaining a considerable part of the revenue from tourism implies a shift in business focus from primarily agricultural activities towards a more recreational character (Rickards and Howden, 2012).

b. Revealed resilience

Revealed resilience is measured ex-post the shocks by observing the changes in the TFP decomposition (Zawalińska et al., 2022). It is accessed by decomposing TFP into technological change and three types of efficiency changes; scale efficiency, allocative efficiency and the rate of change in technical efficiency. Farm demonstrates revealed resilience through observable responses to the challenges. If the TFP decomposition shows no substantial changes and the system maintains its performance by withstanding the situation, it indicates *revealed resilience* and the system is therefore robust. The technological change and efficiency components maintain similar proportions, and TFP remains non-declining or even grows. In case the TFP path declines then the system is considered non-robust, if there is no change in TFP composition. On the contrary, the adaptive system shows revealed resilience by showcasing substantial changes in TFP composition. In this case, technological change and efficiency components exhibit notable shifts yet the overall TFP remains non-declining.

II.1. Stochastic Frontier Analysis and Total Factor Productivity

II.1.1 Stochastic Frontier Analysis (SFA)

To explores the trade-offs of between farm resilience, farm efficiency and TFP, Stochastic Frontier Analysis (SFA) is used (Lambarraa-Lehnhardt, 2023). Following the SFA, the farm's production process is assumed to be influenced by two error components (e.g., Aigner et al., 1977; Coelli et al., 2005). The initial error component is the technical inefficiency error term (u), signifying the deviation to which current production falls short of optimal achievable production (frontier). While, the second error term is the symmetric error component (v), representing unfavorable factors such as unobserved inputs beyond the farm's control or potentially excluded variables (Battese and Coelli, 1995, Meeusen and van den Broeck, 1977, Kim and Schmidt, 2000).

The stochastic production function, can be expressed as (Greene, 2005):

$$\ln y_{it} = [(\alpha + \omega_i) + f(x_{jit}, t; \beta)] \exp(v_{it} - u_{it}) \quad (5)$$

where y_{it} represents the output of the i^{th} farm ($i=1, \dots, N$) in year t ($t=1, \dots, T$); α is a group specific constant; ω_i is a time invariant, firm specific random term12 meant to capture cross farm heterogeneity; the quantity of the j^{th} input ($j=1, \dots, J$) used by the i^{th} farm in year t is represented by x_{jit} ; β is the vector of unknown parameters to be estimated; and $e_{it} = v_{it} - u_{it}$ is the above mentioned composite stochastic error term. The technical inefficiency (u_{it}) in the stochastic production frontier is expressed as fellow.

$$u_{it} = \delta_0 + \sum_{m=1}^M \delta_m z_{mit} + \varphi_{it} \quad (6)$$

where z_{mit} are explanatory variables ($m=1, \dots, M$) of farm i ($i=1, \dots, N$) in year t ($t=1, \dots, T$); δ_0 and δ_m are unknown parameters; and $\varphi_{it} \sim N(0, \sigma^2)$ is a random variable defined by a half normal distribution such that $\varphi_{it} \geq -(\delta_0 + \sum \delta_m z_{mit})$. Integrating equation (6) into equation (5) results in the following model specification:

$$\ln y_{it} = (\alpha + \omega_i) + f(x_{jit}, t; \beta) + v_i - u_{it}(z_{it}; \delta) \quad (7)$$

II.1.2 Total Factor Productivity (TFP)

Farm productivity is a measure of the agricultural output generated by a farm relative to its available resources i.e., land, labor, capital, and machinery. The production function is used to further decompose TFP. TFP can be calculated after estimating the stochastic frontier model following Lambarraa et al. (2007, 2011). The calculation of TFP is composed of four parts: rate of technical change, rate of change in technical efficiency, scale of economies, and allocative efficiency.

TFP can be defined as the difference between the rate of change of output and the rate of change of an input quantity index based on Divisa Index as:

$$\dot{TFP} = \dot{y} - \sum_k S_k x_k \quad (8)$$

Where a dot on the variable indicates its rate of change and $S_k = W_k * X_k / E$, is the observed expenditure share of input k , being $E = \sum W_k * X_k$ the total expenditure and W_k the price of input k . By differentiating the equation (1) with time and using the above-given expression, we can write TFP as:

$$\dot{TFP} = T\Delta + (\varepsilon - 1) \sum_k \left(\frac{\varepsilon_k}{\varepsilon} \right) \dot{x}_k + \sum_k \left[\left(\frac{\varepsilon_k}{\varepsilon} \right) - S_k \right] \dot{x}_k + TE\Delta \quad (9)$$

where,

$$T\Delta = \frac{\partial \ln f(x, t; \beta)}{\partial t} , \quad \varepsilon = \varepsilon(x, t; \beta) = \sum_k \varepsilon_k (x, t; \beta), \text{ and } TE\Delta = -\frac{\partial u}{\partial t} ,$$

$$\varepsilon_k = \varepsilon_k (x, t; \beta) = \frac{x_k (\partial f(x, t; \beta)) / \partial x_k}{f(x, t; \beta)}$$

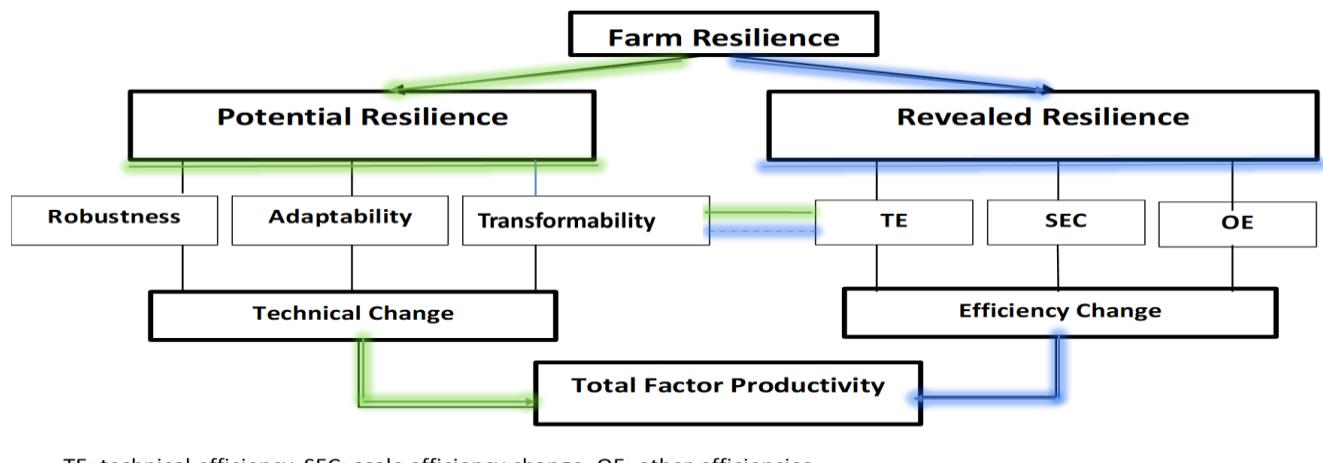
Here, $T\Delta$ is the rate of technical change which is a measure of the maximum attainable output. The second sum represents the scale of economies. E_k , represents the output elasticity to input x_k . The third term is allocative efficiency. It is a measure of the impacts of a deviation in input prices from the value of their marginal products. Lastly, technical efficiency change is the rate of change in technical efficiency which is a measure of the gap between the production frontier and the firm's actual production.

II.1.3 Trade off and synergies between farm resilience, total factor productivity and efficiency

Figure 2 illustrates the concept of farm resilience, showcasing the trade-offs and synergies between potential resilience and revealed resilience. It breaks down potential resilience into three key capacities: robustness, adaptability, and transformation. These capacities contribute to the farm's ability to withstand

and recover from shocks. Revealed resilience, on the other hand, involves technical efficiency (TE), efficiency change, scale efficiency change (SEC), and other efficiencies (OE).

The figure suggests that the components of potential resilience, such as robustness, adaptability, and transformability, play a role in influencing technical efficiency. Moreover, the combined impact of technical efficiency and the efficiency change represented by farm revealed resilience contributes to the overall TFP. In another way, the technical change represented by farm potential resilience also contributes to TFP. This holistic view underscores this trade off and synergies between different aspects of farm resilience, efficiency, and farm productivity



Source: Authors

Figure 2. Trade off and synergies between farm potential and revealed resilience, TFP and efficiency

III. Empirical application

As noted above, the aim of this paper is to quantify the relation among resilience, technical efficiency, and total factor productivity of Italian olive farms. Farm level data is taken from EU Farm Accounting Data Network (FADN). Information collected from each farm encompasses physical, structural, economic, and financial data. FADN (2006) offers representative data on EU agricultural holdings across three dimensions: region, economic size, and type of farming. The sample consists of unbalanced panel data of 1412 observations from 2013 to 2019. The sample data was prepared in order to assess calculate the resilience capacities, estimate the stochastic frontier model, and decompose the TFP growth. To assess farm resilience, we aggregate various resilience capacity indicators into composite

measures. These composite indicators provide valuable insights into the farm's ability to withstand and recover from shocks. Before running Principal Component Analysis (PCA), it was necessary to run KMO and Bartlett's tests to check the adequacy of the statistical technique. PCA is a suitable method if Bartlett's test rejects the null hypothesis (at a 5% level) of no intercorrelations between indicators (Hair et al., 2014) and the KMO value exceeds 0.5 (Kaiser, 1974). The p-values were recorded at 0.000 and the KMO was 0.621 which is greater than the benchmark. Therefore, PCA is the suitable statistical method for calculating composite resilience indicators in this paper. The composite resilience indicators are derived using PCA approach proposed by Slijper et al. (2022). The suitability of PCA for assigning indicator weights is confirmed, as all KMO values surpassed 0.500, and the Bartlett test yielded significant intercorrelations between indicators (p-values<0.01).

SFA is used to estimate farm technical efficiency and to explore the impact of potential influence of resilience measures on farm productivity. The production function (equation 5) is specified as the Trans-log form. Trans-log model shows positive values for each of the four inputs used in the production frontier whereas, in the case of the Cobb-Douglas, the land variable showed a negative coefficient and insignificant p-value which lacks theoretical basis. The output variable is measured as total revenue (in €). Vector x_{jut} is determined as a (1×4) vector that consists of four inputs. These inputs represent the production frontier of the efficiency analysis. x_1 represents the Land; x_2 , is the labor input measured in labor hours per year; x_3 , representing fertilizers and pesticides; and x_4 , variable crop-specific inputs other than fertilizers. The output and the input variables are trimmed at 10% to reduce the effect of outliers. Trimming was checked against a benchmark of 5% and 10%, however 10% was selected as the best fit. The technical inefficiency component consists of five variables, each of them are recorded as dummy variables where 1, indicates a positive response and 0 indicates a no/negative response (Z_1 , robustness; Z_2 , adaptability; Z_3 , transformation dummy; Z_4 , subsidies dummy and Z_5 , renting machinery dummy). As suggested by (Madaan et al., 2023) renting machinery can help increase farm income and efficiency. Additionally, based on research of (Kumbhakar et al., 2023), subsidies tend to increase farm's efficiency and profitability. Furthermore, a time trend variable is also included that represents technical change. The above equations also include the cross-section of inputs with other inputs. Technical change is expressed by trend variable t .

Currently, the model might suffer from reverse causality. To address potential issues of reverse causality in the model specification, the study employs a control function approach. This approach aims to examine whether the resilience capacity indicators themselves contribute to endogeneity in the technical efficiency models. To achieve this, a two-stage approach, inspired by the works of Papke and Wooldridge (2008), Wooldridge (2015), and Slijper et al. (2022), is adopted. In the first stage, a reduced form equation is estimated for each resilience capacity variable, utilizing pooled Ordinary Least Squares (OLS) regression. In the second stage, the residuals obtained from the first stage are integrated into the technical inefficiency

function model. This approach helps to mitigate any potential bias arising from endogeneity, thereby enhancing the reliability of the estimates and facilitating a more accurate analysis of the relationship between the resilience indicators and technical inefficiency. The reduced form is given by:

$$y_{2it} = \lambda_{sit} + \delta_m Z_{mit} + t + \tau_{it} \quad (10)$$

where y_{2it} are the endogenous composite resilience indicators i ($i=1,\dots,N$) indicates a certain farm; t ($t=1,\dots,T$) represents a time dummy to allow for different period intercepts; m ($m=1,\dots,M$) are other explanatory variables of technical inefficiency besides the estimated resilience capacity variable; s_{it} is a vector of instrumental variables, in this paper, the first lags of the composite resilience indicators; and τ_{it} is the error term.

To specify the model, we carried out different statistical tests using the generalized likelihood ratio (L-R). The results of test outcomes are presented in Table 1.

The first tested hypothesis is the presence of constant returns to scale is rejected at 1% significance level, which means that there are no constant returns to scale. The second hypothesis of the absence of inefficiency effects is rejected at 1%, which reveals that inefficiency effects are not absent from the model. The last hypothesis of zero-technical change is rejected at 5%, this indicates that the Italian olive farms show non-neutral technical progresses.

Table 1. Model specification tests

Hypothesis	LR test-statistic	P-value
Constant returns-to-scale, (i.e., $\sum k \beta_k = 1$)	18.11	0.0001
Absence of inefficiency effects, (i.e., $\gamma = \delta_1 = \dots = \delta_M = 0$)	39.93	0.0000
Zero-technical change, (i.e., $\beta_t = \beta_{kt} = 0 \forall k$)	11.49	0.0424

Source: Authors

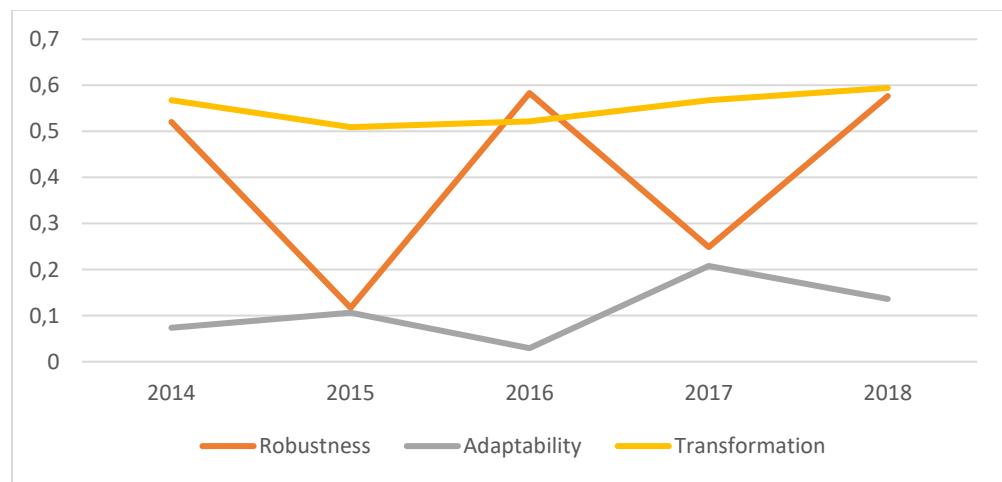
For TFP analysis, the equation (5) is partially derivative with respect to the time variable t , which represent the technical change. Following the framework of Lambarraa et al. (2007, 2011), each of the four components are calculated. The TFP growth is the summation of its four components. To quantify the relationship between TFP and resilience indicators, the OLS estimation is utilized. The estimated results derived from the Trans-log model are given in the following section along with regression results.

VI. RESULTS

VI.1 Potential resilience capacity indicators

The calculated composite potential resilience capacity indicators suggest that Italian farms exhibit higher resilience in terms of transformability, with an indicator of 0.55, followed by robustness in absorbing economic shocks (0.398) and adaptability to new circumstances (0.259).

Figure 3 depicts the changes in potential resilience capacities within Italian olive farms over time. The Robustness dimension exhibits oscillations from one year to another, influenced by the alternation in olive production (biennial bearing). This alternation impacts farm profitability and, consequently, its robustness. In the case of Italian farms, this natural phenomenon might be more pronounced due to climate change and the age of olive trees. Adaptability, reflecting alterations in input composition and production processes, demonstrates a contrasting evolution to robustness, but with minor fluctuations. In years with low production, the adaptability of Italian olive farms increases, but not sufficiently to offset the reduction in robustness. However, there is a general increasing trend from 2014 to 2018, showing an 84% overall rise. Transformability shows a gradual increase of 4.6% during the period, indicating mild internal structural changes in Italian olive farms to adapt to risks.



Source: Authors

Figure 3. The evolution of potential resilience capacities in Italian olive farms

VI.2 SFA and TE estimation: impact of resilience capacities

The results obtained from estimating the Translog stochastic frontier model for Italian olive farms are presented in Table 2. First-order parameters are positive and statistically significant, indicating an

increase in production with the corresponding inputs. In the inefficiency model, the impact of renting machinery on Italian olive farms' technical efficiency is positive, suggesting that farms with more rented machinery tend to be more efficient. This finding aligns with the results of Madaan et al. (2023).

On the other hand, subsidies have a negative impact on farm technical efficiency, consistent with the findings of Rizov et al. (2013). The provision of subsidies may diminish the motivation to adopt new technologies or enhance farming practices, prioritizing short-term benefits at the expense of long-term farm performance.

Robustness has a negative impact on the technical efficiency of Italian olive farms. This result can be explained by the oscillation of robustness influenced by the alternation in olive production during the studied period, which impacts the farm's capacity to utilize its inputs optimally in the production process to achieve the maximum possible output level. The adaptability indicator also has a negative impact on farm technical efficiency. Similarly, adaptability often requires reallocating resources to address new challenges or opportunities. This reallocation can disrupt established workflows and may result in temporary inefficiencies as resources are redirected and adjusted to new priorities. Reorganizing teams or changing roles can also cause a temporary decrease in technical efficiency until everyone adapts to the new structure. Adaptability solutions might not be fully optimized to address the requirements of olive farms during shocks, causing disruptions in output pre and post-shock. In terms of adaptability, building adaptive practices might lead to greater long-term flexibility, but the process of adapting and learning new techniques can initially be less efficient. Adopting new methods requires additional training, which could temporarily affect operational efficiency. Transformability to a new farm type also decreases efficiency, as organic farms are deemed less efficient compared to conventional farming systems. An entire shift in the farming system can set back farm efficiency for years until the strategies are optimally designed.

Table 6. Maximum likelihood estimates of the stochastic frontier model for Italian olive farms

Variables	Parameters	Estimates	Standard error
Frontier production function			
Constant	α	-7.894	3.539***
Labor	β_{LB}	2.660	0.8416***
Land	β_L	0.1649	0.08842*
Fertilizers & Pesticides	β_{FP}	0.2973	0.1636***
Other-specific cost (sc)	β_{sc}	.281503	0.0930*

Technical change	β_T	-0.0524	0.0978
Time x Land	β_{TL}	-0.0019	0.0017
Time x Labor	β_{TLB}	-0.0041	0.0150
Time x Fertilizers & Pesticides	β_{TFP}	-0.0003	0.0047
Time x Other-specific costs	β_{TSC}	0.0117	0.008
Other specific cost x Land	δ_{SCL}	-0.0142	0.0057***
Other specific-cost x Labor	δ_{SCLB}	-0.0290	0.0454
Other specific-cost x Other specific-cost	δ_{SCSC}	0.098	0.0220***
Other specific-cost x Fertilizers & Pesticides	δ_{SCFP}	-0.095	0.0141***
Fertilizers & Pesticides x Land	ε_{FPL}	0.003	0.0026
Fertilizers & Pesticides x Labor	ε_{FPLB}	0.0379	0.0231
Fertilizers & Pesticides x Fertilizers & Pesticides	ε_{FPFP}	0.0102	0.0054*
Land x Land	ω_{LL}	-0.0112	0.0046***
Land x Labor	ω_{LLB}	0.007	0.0099
Labor x Labor	ϕ_{LBLB}	-0.1468	0.0588***

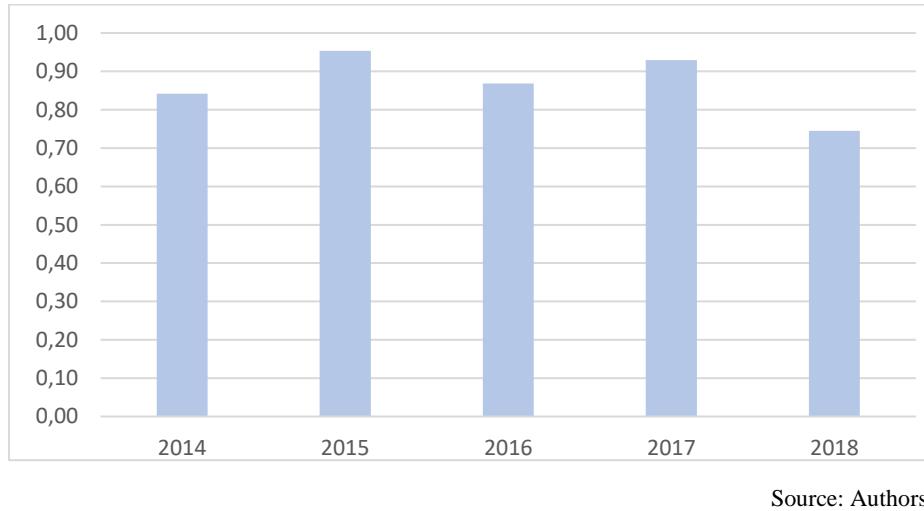
Technical inefficiency function

Constant	δ_0	-7.766	1.596***
Renting machinery	δ_{RM}	-1.117	0.2815***
Subsidies	δ_{SB}	0.7874	1.280***
Robustness	δ_R	5.914	0.7900***
Adaptability	δ_A	0.5315	0.2240***
Transformability	δ_T	0.202	0.1946*
Sigma squared	σ^2	0.203	.0080***
LR-test		-350.675	
Mean technical efficiency		0.861	

Notes: ***, ** and * indicate that the parameter is significant at 1%, 5%, and 10% respectively.

Source: Authors

The evolution of the estimated technical efficiency scores are presented in Figure 4. The predicted technical efficiency takes the average value of 86.1%, implying that output could increase substantially if technical inefficiency were eliminated. The fluctuations in technical efficiency are related to farm potential resilience capacities to deal with shocks, especially robustness and adaptability.



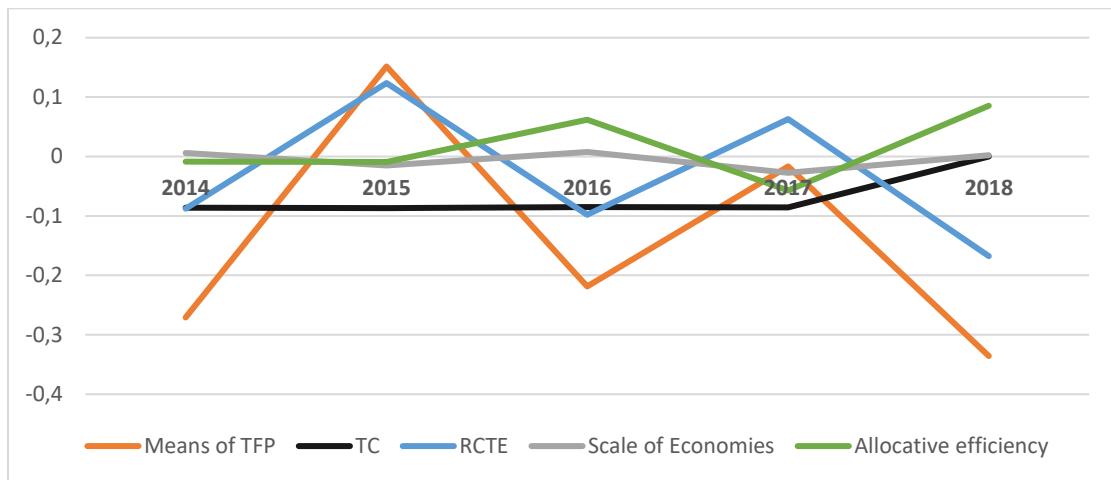
Source: Authors

Figure 4. The evolution of potential resilience capacities in Italian olive farms

VI.3 TFP decomposition and resilience dynamics

The evolution of the TFP decomposition over the years is reported in Figure 5. TFP is the aggregated sum of the rate of technical change, scale economies, allocative efficiency, and the rate of change in technical efficiency. TFP exhibits a fluctuating pattern over the years, which can be attributed to the natural tendency for alternate bearing, resulting in high productivity in one year and low productivity in the next.

The rate of technical change indicates a weak adoption of technology in the olive sector of Italy, with a slight improvement in the last year. The rate of change in technical efficiency follows a similar pattern to the total factor productivity of the farm. When the farm utilizes its set of inputs efficiently, its total factor productivity improves. On the other hand, allocative efficiency and scale economies have a negative impact on TFP growth.



Source: Authors

Figure 1. Changes in TFP components over the years

Table 7 illustrates the dynamics of the evolution of TFP in comparison to potential resilience capacities (robustness, adaptability, and transformability) over the years.

Table 7. Analysis of the dynamics of TFP & resilience indicators

Years	2014-2015	2015-2016	2016-2017	2017-2018
Potential resilience capacities	Non-declining TFP	Declining TFP	Non-declining TFP	Declining TFP
Robustness	Drastic decrease	Drastic increase	Drastic decrease	Drastic increase
Adaptability	Increase	Decrease	Increase	Decrease
Transformability	Partial decrease	Partial increase	Relatively Stable	Partial increase

Source: Authors

The changes in these resilience capacities correspond to whether TFP is non-declining or declining during each respective period. For example, in the year 2014-2015, TFP declined alongside a drastic decrease in Robustness, while adaptability increased. In contrast, in the following year (2015-2016), TFP declined significantly with a decrease in adaptability and a drastic increase in Robustness. These patterns suggest a potential tradeoff between farm resilience capacities and TFP, with the fluctuations in resilience indicators coinciding with changes in TFP over the observed years. We observe a direct impact of farms' adaptability on TFP growth. Changes in a farm's input composition, production, marketing, and risk management directly result in either an increase or decrease in input composition and production processes,

impacting TFP growth. However, the other capacities reflected by Robustness and Transformation do not seem to directly influence TFP movement.

V. CONCLUSION

This paper explores the synergies among resilience, technical efficiency, and total factor productivity (TFP) in Italian olive farms using data from the FADN for the period 2013-2019. The study applied Principal Component Analysis (PCA) to derive composite potential resilience indicators and employed a two-stage control function approach to address potential issues of reverse causality. The stochastic frontier model was employed to estimate technical efficiency and analyze the impact of potential resilience measures on farm productivity.

The calculated potential resilience capacity indicators revealed that Italian olive farms exhibit higher resilience in terms of transformability, followed by robustness and adaptability. The evolution of these capacities over time indicated fluctuations influenced by biennial bearing and external factors like climate change. From the results of stochastic frontier model, we can see that resilience capacity indicators have impact on technical efficiency. Robustness and adaptability negatively affected technical efficiency, indicating challenges related to optimal input utilization during periods of economic shocks or adaptation. Transformability to a new farm type also decreased efficiency, highlighting the complexities of transitioning farming systems. Renting machinery positively influenced technical efficiency, aligning with prior research. In contrast, subsidies had a negative impact, potentially due to short-term prioritization over long-term farm performance.

The examination of TFP growth revealed a fluctuating pattern attributed to natural tendencies like alternate bearing. The rate of technical change indicated a weak adoption of technology in the olive sector, while changes in technical efficiency correlated with TFP growth. A tradeoff between farm resilience capacities and TFP emerged, particularly with Adaptability influencing TFP positively.

In conclusion, this study contributes to the understanding of the complex interaction between resilience, technical efficiency, and TFP in Italian olive farming. The findings underscore the importance of balancing efficiency and resilience, acknowledging the challenges posed by external shocks and transitions in farming practices. The results provide valuable insights for policymakers, farmers, and researchers seeking sustainable and resilient agricultural practices in the face of evolving challenges. Policymakers should incentivize and facilitate the adoption of modern agricultural technologies in the Italian olive sector. Support programs, training initiatives, and subsidies for advanced machinery can contribute to increased productivity and competitiveness. However, subsidies programs need to be carefully designed. Focus should be on promoting long-term sustainable practices rather than solely emphasizing

short-term gains. Monitoring and evaluation mechanisms should be in place to assess the effectiveness of subsidies in fostering innovation and efficiency. Farmers should be equipped with strategies and resources to navigate economic shocks and adapt to the changes. Training programs, insurance schemes, and collaborative networks can enhance farmers' capacity to withstand uncertainties and improve its resilience capacities especially robustness and adaptability. Policies should facilitate and support the transition process posed by transformability to new farm types. Financial incentives, technical assistance, and knowledge-sharing platforms can aid farmers in adopting new farming systems. Long-term benefits of sustainable and resilient farming practices should be emphasized to encourage gradual transitions. The climate-resilient agricultural practices need to be prioritize to face the impacts of shocks such as climate change. Investment in research and development of climate-adaptive technologies, water management strategies, and sustainable farming practices can contribute to the long-term sustainability of Italian olive farming. Establishing a robust monitoring and extension service system is essential. For that, the FADN dataset needs to be integrated to take into consideration other aspects related to sustainability and resilience aspects such as environmental, social, and behavioral indicators to help in the establishment of a strong monitoring system and provide valuable data for evidence-based policymaking. Future research needs to focus also on more collaborative research initiatives involving different stakeholders such as researchers, farmers, policymakers, and the industry.

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