ΕΛΛΗΝΙΚΗ ΔΗΜΟΚΡΑΤΙΑ / HELLENIC REPUBLIC
ΕΠΙΤΡΟΠΗ ΑΝΤΑΓΩΝΙΣΜΟΥ
HELLENIC COMPETITION COMMISSION

Working Paper Series
No. 1/2025

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HCC/WKP(2025) 1
September 2025

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www.epant.gr

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Price dependence among the major EU extra virgin olive oil markets: A DCC-GARCH approach

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30 September 2025

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Abstract

The present working paper examines the interdependence of extra-virgin olive oil prices in Greece, Italy and Spain, the three largest European producers. Unit root tests confirm that all national price series are integrated of order one. Johansen's cointegration analysis reveals a single long–run equilibrium linking Greece and Spain. On the other hand, Italy shows no cointegration with either partner. VECM is estimated for the Greece-Spain pair, highlighting a significant adjustment in Greece but not in Spain. VAR models describe the short–run dynamics between Greece–Italy and Italy–Spain. To capture volatility clustering and co-movements, the DCC–GARCH methodology and asymmetric extensions to the residuals are used. The results indicate a strong persistence in conditional variances across all markets, with Italy showing a greater sensitivity to new shocks and Spain exerting stronger short–run influence. The correlations are highly persistent and largely symmetric, with only weak evidence of asymmetric effects. Overall, Spain emerges as the leading market, driving short–run adjustments across the Mediterranean region.

Keywords: Extra virgin olive oil; Price dependence; Asymmetry;

JEL classification: C14, Q13, L66

1 Introduction

There is an emerging consensus that the international agri-food system is becoming more vulnerable to extreme events of price volatility. The unprecedented surge in agricultural commodity prices following COVID-19 and the Russian invasion of Ukraine has renewed interest in analyzing the interactions of food markets. In addition, the recent inflationary pressures on olive oil prices are largely attributed to adverse weather conditions, resulting in decreased production in major EU producer countries, increased producer prices and subsequently affected import and retail prices.

As agricultural markets become more integrated globally, food price shocks can transfer to domestic markets much faster and with greater intensity (von Cramon-Taubadel, Stephan and Goodwin, Barry K., 2021). There is overwhelming evidence that volatility for many major internationally traded food commodities has increased in recent years. In economic theory, volatility signifies variability and uncertainty (Kose et al., 2003). Uncertainty is inherent in agriculture due to its nature; unpredictable extreme weather events such as droughts and natural disasters such as, floods, can greatly influence production and, consequently, agricultural prices. Olive oil production also shows significant annual fluctuations due to the cyclical nature of olive cultivation (non-steady yield of olive trees). Furthermore, the climate crisis appears to exert significant pressure on olive oil prices, as well as on other agricultural products. Such episodes of extreme price volatility can pose a significant threat to global food security and raise concerns about the potential costs of food market globalization.

At the same time, agricultural commodities form the basis for farmers' income, particularly in developing countries. Events of extreme price volatility have negative implications for the economic welfare of many households in these countries and are a significant threat to food security. The impact falls heavier on the poor, as households in extreme poverty lack the capacity to substitute for lower-cost food items, forcing a trade-off between reducing dietary quality or quantity and diverting funds from other essential non-food expenditures like health and education (Lele et al., 2016).

Within the EU, Greece, Italy, and Spain were among the countries most affected by the recent economic crisis. The budgetary constraints imposed by the crisis have made it significantly more difficult for these governments to intervene and provide financial support to agricultural producers during periods of extreme price volatility.

In agricultural economics, empirical findings indicated that volatility spillovers between commodities are significant during periods of extreme world market volatility (Rapsomanikis and Mugera, 2011; Rapsomanikis, 2011). Regarding the olive oil market, Emmanoulides and Fousekis (2013) utilized the statistical tool of copulas to assess the degree and the structure of price dependence in the principal EU olive oil markets (Spain, Italy and Greece) for the case of virgin and lampante olive oil. According to their results, prices are likely to boom together, but not to crash together. This is true especially for the prices of the two most important players, Italy and Spain. Additionally, their finding of asymmetric price co-movements implies that the three principal spatial olive oil markets in the European Union cannot be thought of as one great pool.

Panagiotou and Stavrakoudis (2023) assessed the strength and mode of price dependence by time scale, among the extra virgin olive oil markets of Italy, Spain, and Greece. For the empirical analysis, monthly prices from the aforementioned countries were used along with the tools of discrete wavelets and non-parametric copulas. The results indicated that (a) price linkages in the short run were significantly different from those in the longer run, with price dependence being more substantial in the longer run, and (b) in the very long run, price shocks of the same sign but of different magnitude were transmitted from Italy to Spain with a higher probability than they were transmitted from Italy to Greece. Accordingly, the time scale affects the intensity as well as the pattern of dependence, pointing this way to asymmetric price co-movement. Regarding the integration of the three markets, the findings of asymmetric co-movement are not consistent with well-integrated markets.

Theofanous and Tremma (2024) employed linear and non-linear econometric techniques to examine for long and short-run relations, market integration and price transmission patterns, between the olive oil markets of Spain, Italy and Greece.

Wholesale data were used for the period January 2000 to April 2022. Stable long-run relations were revealed between the examined price pairs. Empirical findings suggested that Spain is the central market. The Non-linear Momentum Threshold Cointegration model identified as the strongest relation the one between the olive oil prices of Italy and Greece. Price transmission was found to be asymmetric for the pairs Spain-Greece and Spain-Italy, whereas symmetry was confirmed for the pair Italy-Greece.

A better understanding of volatility spillovers between global agri-food markets can assist in policy formulation. Despite the importance of this issue, the number of studies on the transmission of price volatility and price interrelationships in spatial EU agri-food markets has been relatively small. Against this background, the objective of this study is to analyze price linkages between the extra virgin olive oil markets of Italy, Spain, and Greece.

In order to account for volatility clustering and price co-movements, we apply DCC–GARCH and asymmetric extensions to the residuals (Rastogi and Kanoujiya, 2023). The DCC-GARCH (Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity) is a powerful and widely used class of multivariate volatility models (Mishra and Murugesan, 2024; Wu et al., 2024; Al-Anezi et al., 2025). Its primary advantages stem from its ability to model the time-varying nature of correlation between multiple series (Kousar et al., 2024; Dhaene et al., 2022).

The DCC-GARCH models realistic, time-varying correlations. This is the core advantage. Price correlations are not constant; they change over time, often clustering during periods of market stress (a phenomenon known as correlation breakdown or increased dependence in downturns). Accordingly, the DCC model explicitly captures this dynamic.

This study is organized as follows. Section 2 describes the situation on the Mediterranean olive oil market. Section 3.1 describes the data and the modeling framework. Section 4 presents the empirical results. The discussion is presented in Section 5 and the conclusions, policy implications, limitations of the study, and future research are presented in Section 6.

2 Mediterranean Olive Oil Markets Triangle

Worldwide olive oil production has averaged 3 million tons, in the last decade. European Union (EU) is the major producer of olive oil, accounting for about 60% of global production (IOC, 2025). Within the EU, Spain, Italy, and Greece are the dominant producers. In 2024/25, these three Mediterranean countries are responsible for about 88% of olive oil production within the EU. Spain with 56%, Italy with 21% and Greece with 11%, account for about 90% of the EU production.

Spain is the world leader in production volume and the leading olive oil producer in the world with an average output of 800-1350 thousand tons per year. It typically produces 50%-60% of the world's olive oil, and in a good year, it can produce around 1.4 million metric tons. The key production region is Andalusia in southern Spain, which produces around 80% of the country's olive oil, with key provinces including Jaén (often referred to as the "World Capital of Olive Oil"), Córdoba and Sevilla. Spanish production is characterized by large-scale, high-density, intensive orchard plantations that allow efficient mechanical harvesting. Famous varietals include Picual, which is robust and high in antioxidants, and Arbequina, which is smooth, fruity, and sweet. Of the total olive oil production in Spain, 34% is extra virgin (European Commission, 2025).

Italy is the second-largest EU producer. Its output is much smaller than that of Spain, usually around 250-350 thousand tons per year. Production is spread across the country, with key areas being Puglia (which produces nearly 50% of Italy's oil), Calabria, Tuscany, Umbria and Liguria. Italy's production is defined by its diversity, boasting over 500 olive varietals. Key varietals include Coratina (pungent, bitter), Frantoio (complex, grassy), Leccino (mild, almondy), and Taggiasca (delicate, sweet). In Italy, 60% of the production is extra virgin olive oil (European Commission, 2025).

Greece is the third largest EU producer. Its average output is 200-300 thousand tons per year, occasionally surpassing Italy in a given year (i.e 2020/21), of which more than 80% is extra virgin (IOC, 2025). It produces very little low-quality lampante oil. Production is dominated by the Koroneiki varietal, a small olive that produces an exceptionally fruity, green, grassy and pungently peppery oil prized for its robust flavor and high polyphenol (antioxidant) content (European Commission, 2025).

European Union is the world's biggest consumer of olive oil, with a share close to 35% (IOC, 2025). Italy, Spain and Greece account for 74% of the olive oil consumption within the EU. Consumption patterns vary by country. Greeks are the world's largest consumers of olive oil, at about 9.3 liters per capita annually; this domestic preference for oil shapes the industry. By comparison, Spain's per capita consumption is 7.5 liters, and Italy's is 7.4 liters (IOC, 2025). Regarding the type of oil consumed, Italy and Greece primarily consume extra virgin olive oil. In contrast, in Spain, the consumption of extra virgin olive oil represents almost 50% of the total domestic consumption of olive oil.

Olive oil trade statistics among Greece, Italy, and Spain are remarkable. Trade flows between Spain and Greece are insignificant when comparing trade flows of these two countries with Italy. In 2023/24, 28% of Spain's exports and 60% of Greece's exports have Italy as their destination. Correspondingly, 73% of Italy's imports come from Spain and Greece (IOC, 2025).

Spain is a prominent supplier, exporting large amounts of bottled oil under its own labels. It also sells a significant portion of its high-quality oil in bulk to other countries such as Italy for blending, bottling, and branding. Spain's worldwide export share is approximately 20% (Panagiotou, 2015).

Greece exports a much larger percentage of its highest quality extra virgin olive oil compared to other countries, although a surprising amount is also sold in bulk to Italy. More than half of Greece's annual olive oil production is exported, but only a small fraction of this reflects the origin of the bottled product. Exports of Spain and Greece to Italy consist to a large degree of extra virgin and virgin olive oil, sold in bulk.

Italy is a massive net importer of olive oil, mainly from Spain, Greece, and Tunisia, for blending and bottling. It is worth mentioning that although Italy is a deficit market within the EU, it is one of the largest exporters of bottled olive oil worldwide, with a share of around 30% (Panagiotou, 2015). Italy is the world leader in marketing, branding, and export value, and is synonymous with high-end olive oil globally. The art of blending oils from different regions and varietals to create a consistent and balanced flavor profile is a quintessential Italian skill. Bulk imports from Spain and Greece are bottled and/or blended by a small number of major Italian companies, and they are distributed worldwide.

As a massive producer, Spain's overall reputation is for reliable quality and value, though it also produces some of the world's finest premium oils. Greece is considered the quality and per capita powerhouse. Among connoisseurs, Greek oil is renowned for its intense, robust flavor and exceptional quality. Its reputation is growing internationally as consumers discover its distinctive character. Italian olive oil is a symbol of quality, culture, and identity. Italian oil is considered a premium product as a result of successful branding, while Greek and Spanish oil is sold in Italy in bulk without any added value.

3 Methodology

3.1 Data

Data were obtained from the European Commission (2025). Data for the empirical application are weekly prices of extra virgin olive oil (measured in euros per 100 kilograms) from Italy, Spain, and Greece. Concerning Portugal data, for extra virgin olive oil, there are only 31 observations during the period 2020-2025. The insufficient number of observations renders the application of the VAR/VECM methodology infeasible. For this reason, Portugal has been excluded from further analysis.

Figure 1 presents the evolution of the prices of extra virgin olive oil for the countries mentioned above.[1] The three price series evolve in a similar way, presenting an increasing trend over the years 2020-2024. The dramatic price increase between 2023-2024 was primarily due to a severe drought in Spain (the world's largest pro-

[1]According to the relevant Regulation by the European Commission, the extra virgin category refers to olive oils obtained from the fruit of the olive tree at the optimum stage of ripening, solely by mechanical or other physical means that do not lead to alteration of the oil and have not undergone any treatment other than washing, decantation, centrifugation or filtration. Extra virgin olive oil has a maximum of 0.8 grams of oleic acid per 100 grams of oil.

ducer) and other Mediterranean countries, which decimated harvests. Following that time period, Spanish and Greek extra virgin olive oil prices exhibit a downward trend, whereas Italian prices are (almost) stable. A combination of improved weather leading to a rebound in Spanish and Greek production and a slight reduction in demand due to consumers adapting to high prices are the main drivers behind the decrease in prices. On the other hand, Italian olive oil is a symbol of quality, culture, and identity. Olive oil from Italy is considered a premium product as a result of successful branding, while Greek and Spanish oil is sold in Italy in bulk without any added value, as mentioned earlier in Section 2. Italian packaging, design, and the allure of "Made in Italy" command premium prices worldwide, with a reputation built on premium branding, stylistic diversity, and a strong link to Italian cuisine and lifestyle. Consumers are willing to pay higher prices for the story and the perceived quality associated with Italian olive oil.

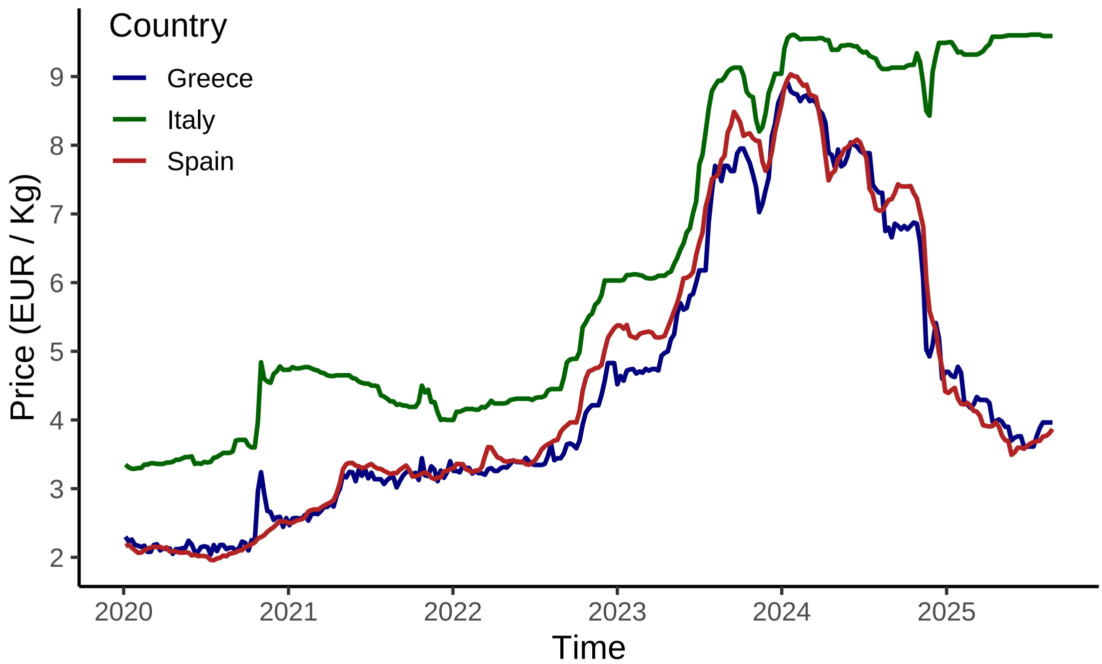

Figure 1: Time series of extra virgin olive oil prices, weekly data between 5/1/2020 and 24/8/2025.

3.2 Stationarity and Cointegration

All time series have been logarithmically transformed tested for unit root at levels and returns (Tsay, 2010). Tradional Johansen test has been also applied in order to determine the order of coordination. Depending on the presence or not of cointegration we follosed a VECM/VAR modeling strategy as described below.(Tsay, 2010).

3.2.1 Non-cointegrated pairs

When the Johansen trace test does not detect cointegration between two price series, a vector error correction model is not appropriate. Instead, we estimate a vector autoregression (VAR) in first differences:

$$\Delta y_t = c + \sum_{i=1}^{p} A_i \Delta y_{t-i} + \varepsilon_t, \tag{1}$$

where Δy_t is the vector of log returns, A_i are coefficient matrices, and ε_t are innovations. As before, the innovations exhibit time-varying volatility. We therefore model their conditional covariance matrix H_t using a multivariate GARCH specification such as the dynamic conditional correlation (DCC–GARCH):

$$\varepsilon_t \,|\, \mathcal{F}_{t-1} \sim (0, H_t), \qquad H_t = D_t R_t D_t, \tag{2}$$

with univariate GARCH dynamics for the variances in D_t and R_t capturing the evolving correlations. This approach allows us to analyse short-run spillovers and volatility transmission between markets that do not share a long-run equilibrium.

3.2.2 Vector Error Correction Model

To analyse the long-run integration and short-run volatility dynamics of olive oil markets, we employ a two-step approach that combines cointegration analysis with a multivariate GARCH framework.

Let y_t denote a $(k \times 1)$ vector of log prices. If the elements of y_t are integrated of order one, $I(1)$, but there exists a linear combination $\beta^\top y_t$ that is stationary, then the variables are cointegrated with cointegration vector β. Johansen's trace test is used to determine the number r of such cointegration relations. The vector error correction model (VECM) is then written as

$$\Delta y_t = \alpha\beta^\top y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t, \tag{3}$$

where α is the $(k \times r)$ loading matrix describing the speed of adjustment toward equilibrium, Γ_i are short-run dynamics, and ε_t are innovation terms.

3.2.3 Conditional Volatility and Correlation

The residuals ε_t are rarely homoskedastic in financial or commodity markets, typically exhibiting volatility clustering. To account for this, we specify their conditional covariance matrix H_t through a dynamic conditional correlation GARCH (DCC–GARCH) model. Specifically, let

$$\varepsilon_t = H_t^{1/2} z_t, \qquad z_t \sim \mathcal{N}(0, I), \tag{4}$$

with

$$H_t = D_t R_t D_t, \tag{5}$$

where D_t is diagonal with univariate GJR–GARCH(1,1) variances

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \gamma_i I_{\{\varepsilon_{i,t-1}<0\}} \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}, \tag{6}$$

and R_t is the time-varying correlation matrix.

3.2.4 Asymmetric DCC Model

The asymmetric DCC (aDCC) specification allows correlations to respond differently to negative shocks:

$$Q_t = (1 - a - b)\bar{Q} + a(z_{t-1} z_{t-1}^\top) + g(n_{t-1} n_{t-1}^\top) + bQ_{t-1}, \tag{7}$$

where $z_t = D_t^{-1}\varepsilon_t$ are standardized residuals, $n_t = \min(z_t, 0)$ captures negative shocks, $\bar{Q}$ is the unconditional correlation of z_t, and (a, b, g) are the DCC parameters. The correlation matrix is then

$$R_t = \mathrm{diag}(Q_t)^{-1/2} Q_t \, \mathrm{diag}(Q_t)^{-1/2}. \tag{8}$$

3.3 Summary

The present study integrates the analysis of equilibrium relations through Johansen cointegration and VECM with a DCC–GARCH modeling of volatility and correlation. The aforementioned approach enables us to examine not only whether olive oil markets share long-run price equilibria but also how volatility and cross-market correlations evolve over time and whether they react asymmetrically to adverse shocks.

All calculations in this study were performed with R (version 4.5.1, R Core Team (2014)).

4 Empirical Results

As a first step, each log-transformed time series is tested for stationarity(Tsay, 2010) at both levels and first differences. The results of the unit root tests are presented below.[2]

4.1 Stationarity

Greece

As we can see in Table 1 the unit root tests for Greece strongly suggest that the log price series are non-stationary, while its first differences (returns) are stationary. For log prices, the ADF and ERS statistics are never significant across specifications and lags, indicating a failure to reject the null of a unit root. The KPSS statistics are consistently large, rejecting the null of stationarity both under level and trend

[2] Shorcuts for unit root tests: i) ADF: Augmented Dickey–Fuller test, ii) KPSS: Kwiatkowski–Phillips–Schmidt–Shin test, iii) Elliott–Rothenberg–Stock test, iV) Zivot–Andrews test

Table 1: Unit root tests for Greece

Test	Types	0	1	2	0	1	2
ADF	none	0.758	0.742	0.719	-15.925***	-11.608***	-10.639***
	drift	-1.300	-1.382	-1.352	-15.940***	-11.630***	-10.682***
	trend	-0.072	-0.204	-0.181	-16.063***	-11.766***	-10.891***
KPSS	mu	21.331	10.700	7.152	0.485*	0.454**	0.444**
	tau	3.781	1.907	1.280	0.211*	0.199*	0.196*
ERS	constant	-0.253	-0.313	-0.308	-11.191***	-7.363***	-6.038***
	trend	-0.475	-0.606	-0.603	-13.657***	-9.435***	-8.080***
ZA	intercept	-3.780	-3.734	-3.735	-16.638***	-12.425***	-11.745***
	trend	-3.666	-3.624	-3.652	-16.391***	-12.147***	-11.381***
	both	-4.304	-4.309	-4.300	-16.691***	-12.485***	-11.828***

specifications. Likewise, the Zivot–Andrews test does not provide evidence against a unit root even when allowing for a possible structural break. By contrast, when applied to returns, all tests uniformly reject the unit root null at the 1% level, with ADF, ERS, and ZA statistics showing very large magnitudes and KPSS failing to reject stationarity. Taken together, the evidence indicates that the Greek olive oil price series is integrated of order one, $I(1)$, and that the appropriate transformation for subsequent modeling is the first difference of the log price.

Italy

Table 2: Unit root tests for Italy

Test	Types	0	1	2	0	1	2
ADF	none	3.142	2.313	2.370	-12.388***	-10.127***	-8.946***
	drift	-0.744	-0.886	-0.900	-12.709***	-10.498***	-9.375***
	trend	-1.075	-1.533	-1.470	-12.696***	-10.492***	-9.373***
KPSS	mu	27.406	13.755	9.199	0.203***	0.158***	0.143***
	tau	2.467	1.242	0.833	0.196*	0.152*	0.138**
ERS	constant	1.950	1.228	1.258	-9.660***	-7.401***	-6.159***
	trend	-1.136	-1.584	-1.532	-11.551***	-9.234***	-7.985***
ZA	intercept	-2.855	-3.004	-2.957	-13.071***	-10.939***	-9.912***
	trend	-1.533	-1.881	-1.815	-12.838***	-10.658***	-9.574***
	both	-2.855	-3.182	-3.118	-13.348***	-10.970***	-9.949***

As shown in Table 2 the evidence for Italy aligns with the view that log prices are non-stationary, while returns are clearly stationary. For the log-level series, the

ADF and ERS statistics remain insignificant across all lag choices and specifications, meaning the null hypothesis of a unit root cannot be rejected. At the same time, the KPSS results are large, rejecting the null of stationarity under both level and trend, reinforcing the $I(1)$ classification. The Zivot–Andrews test, even when allowing for a possible break in intercept or trend, does not overturn this conclusion, as the statistics remain far from critical values. In contrast, the results for returns are unambiguous. The ADF, ERS, and ZA tests strongly reject the null of a unit root at the 1% level across all lags and specifications, while the KPSS statistics are small enough to accept stationarity. Overall, the Italian olive oil price series behaves as an integrated process of order one, and the stationary transformation for further analysis is the first difference of the log price.

Spain

Table 3: Unit root tests for Spain

Test	Types	0	1	2	0	1	2
ADF	none	1.515	0.716	0.729	-8.535***	-6.936***	-6.613***
	drift	-1.651	-1.365	-1.519	-8.570***	-6.983***	-6.670***
	trend	1.603	-0.101	-0.306	-8.761***	-7.213***	-6.946***
KPSS	mu	20.804	10.425	6.963	1.988	1.246	0.961
	tau	4.237	2.130	1.427	0.717	0.455	0.354
ERS	constant	0.184	-0.253	-0.329	-8.054***	-6.539***	-6.197***
	trend	0.821	-0.502	-0.691	-8.730***	-7.181***	-6.904***
ZA	intercept	-4.994**	-4.285	-4.181	-9.543***	-7.953***	-7.754***
	trend	-3.938	-3.777	-3.661	-9.174***	-7.556***	-7.331***
	both	-4.371	-4.086	-4.037	-10.114***	-8.563***	-8.472***

As reported in Table 3, the Spanish series also display clear evidence of non-stationarity in log prices, contrasted with stationarity in returns. In levels, the ADF and ERS tests fail to reject the null of a unit root at any lag or specification. The KPSS statistics are large across both level and trend settings, leading to a rejection of stationarity. The Zivot–Andrews test suggests at most weak evidence of a break, with one intercept specification close to significance, but overall the results are consistent with a unit root. When applied to returns, the conclusions reverse. The ADF, ERS, and ZA statistics are all highly significant across lags, strongly rejecting the null hypothesis of a unit root. The KPSS test values are lower than in levels, consistent with stationarity. Taken together, these results show that Spanish olive oil prices follow an integrated process of order one, and that the appropriate stationary representation is obtained from the first difference of the log price.

4.2 Cointegration

Greece–Italy

Table 4: Johansen cointegration test for Greece–Italy

Test type	Hypothesis	Statistic	10%	5%	1%
Trace	$r = 0$	6.50	22.76	25.32	30.45
	$r \leq 1$	2.74	10.49	12.25	16.26
Max–eig	$r = 0$	3.76	16.85	18.96	23.65
	$r \leq 1$	2.74	10.49	12.25	16.26

In Table 4 the Johansen tests provide no evidence of cointegration between the Greek and Italian prices. Both the trace and maximal eigenvalue statistics fall well below the 10% critical values,[3]

indicating that the null hypothesis of no cointegrating relation cannot be rejected. This result holds under both the "long-run" and "transitory" specifications, as the eigenvalues are small and the test statistics remain insignificant across cases. Accordingly, the Greece–Italy pair should be modeled without an error correction term, relying instead on a VAR in differences to capture the short-run dynamics between the two markets.

Table 5: Johansen cointegration test for Greece–Spain

Test type	Hypothesis	Statistic	10%	5%	1%
Trace	$r = 0$	32.14***	22.76	25.32	30.45
	$r \leq 1$	2.92	10.49	12.25	16.26
Max–eig	$r = 0$	29.22***	16.85	18.96	23.65
	$r \leq 1$	2.92	10.49	12.25	16.26

Greece–Spain

As shown in Table 5 both the trace and maximal eigenvalue tests reject the null of no cointegration for the Greece–Spain pair at the 1% level. The $r = 0$ statistics (32.14 and 29.22, respectively) exceed the 1% critical values, while the $r \leq 1$ statistics remain far below their thresholds, implying a single cointegrating relation ($r = 1$). These findings are robust across the "long-run" and "transitory" specifications, which yield identical test statistics in this case. Accordingly, Greece and Spain share a stable long-run equilibrium, and the appropriate mean specification is a VECM with rank one, augmented by short-run dynamics in differences.

Italy–Spain

Table 6: Johansen cointegration test for Italy–Spain

Test type	Hypothesis	Statistic	10%	5%	1%
Trace	$r = 0$	6.85	22.76	25.32	30.45
	$r \leq 1$	3.25	10.49	12.25	16.26
Max–eig	$r = 0$	3.60	16.85	18.96	23.65
	$r \leq 1$	3.25	10.49	12.25	16.26

In Table 6 the Johansen tests do not provide evidence of cointegration between Italian and Spanish prices. The trace and maximal eigenvalue statistics are well

[3] Critical values for two variables, at 5%:

Null hypothesis	Trace 5% CV	Max-Eig 5% CV
$r = 0$	15.41	14.07
$r \leq 1$	3.76	3.76

and at 10%:

Null hypothesis	Trace 10% CV	Max-Eig 10% CV
$r = 0$	13.43	12.30
$r \leq 1$	2.71	2.71

below the 10% critical values, both for the $r = 0$ and $r \leq 1$ hypotheses. Thus, the null of no cointegrating relation cannot be rejected, regardless of whether the "long-run" or "transitory" specification is applied. Accordingly, the Italy–Spain pair should be modelled using a VAR in differences, as no long-run equilibrium relationship is supported by the data.

4.3 VECM and DCC–GARCH models

4.3.1 Greece–Italy

We estimated a bivariate DCC–GARCH(1,1) model(Tsay, 2010) for the Greece–Italy return series.[4] Each margin follows a univariate GARCH(1,1),

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}, \quad i \in \{EL, IT\}, \tag{9}$$

while the conditional correlations evolve according to

$$Q_t = (1-\alpha-\beta)\bar{Q}+\alpha\, \varepsilon_{t-1}\varepsilon_{t-1}'+\beta\, Q_{t-1}, \qquad R_t = \mathrm{diag}(Q_t)^{-1/2} Q_t\, \mathrm{diag}(Q_t)^{-1/2}. \tag{10}$$

Table 7: DCC(1,1) with GARCH(1,1) margins for Greece–Italy

Parameter	Estimate	Std. Error	t-value	p-value
μ_{EL}	0.000	0.001	0.000	1.000
ω_{EL}	0.000	0.000	2.771	0.006
$\alpha_{EL,1}$	0.238	0.193	1.234	0.217
$\beta_{EL,1}$	0.759	0.097	7.824	0.000
μ_{IT}	0.000	0.001	0.000	1.000
ω_{IT}	0.000	0.000	0.285	0.776
$\alpha_{IT,1}$	0.135	0.049	2.731	0.006
$\beta_{IT,1}$	0.860	0.054	15.867	0.000
$dcca_1$	0.014	0.010	1.392	0.164
$dccb_1$	0.965	0.017	58.244	0.000

The DCC–GARCH(1,1) specification in equation 9 provides a flexible way to capture both individual market volatility dynamics and time–varying cross–market

[4]There is empirical evidence that GARCH(1,1) captures effectively the ARCH effect and higher order models rarely improves forecasts

Table 8: aDCC(1,1) with GARCH(1,1) margins for Greece–Italy

Parameter	Estimate	Std. Error	t-value	p-value
μ_{EL}	0.000	0.001	0.000	1.000
ω_{EL}	0.000	0.000	2.752	0.006
$\alpha_{EL,1}$	0.238	0.196	1.214	0.225
$\beta_{EL,1}$	0.759	0.104	7.265	0.000
μ_{IT}	0.000	0.002	0.000	1.000
ω_{IT}	0.000	0.000	0.289	0.772
$\alpha_{IT,1}$	0.135	0.049	2.747	0.006
$\beta_{IT,1}$	0.860	0.054	15.817	0.000
$dcca_1$	0.014	0.010	1.443	0.149
$dccb_1$	0.965	0.052	18.716	0.000
$dccg_1$	0.000	0.061	0.000	1.000

correlations. In the marginal GARCH equations, the estimates reported in Table 8 show that both Greece and Italy exhibit strong volatility persistence: the β parameters are large and highly significant ($\beta_{EL} = 0.76$, $\beta_{IT} = 0.86$). This indicates that volatility shocks decay only slowly and that periods of high volatility tend to cluster. The ARCH coefficient for Italy ($\alpha_{IT} = 0.135^{**}$) is significant, implying that Italian volatility responds more strongly to recent innovations, whereas the corresponding term for Greece is weaker and not significant. This asymmetry in responses suggests that the Italian market is more sensitive to contemporaneous shocks. On the other hand, Greek volatility is mainly driven by its past.

Turning to the correlation dynamics, the DCC parameters in Table 7 reveal very high persistence ($dccb_1 = 0.965^{***}$), whereas the short–run response to new shocks is small and insignificant ($dcca_1 = 0.014$). This pattern implies that conditional correlations are highly stable, governed mostly by their long memory rather than immediate reactions. The asymmetric extension in Table 8 includes the $dccg_1$ term, which tests whether negative shocks affect correlations differently from positive ones. The estimate is essentially zero and not significant, and a likelihood–ratio test confirms that the symmetric DCC model suffices. Overall, the results from Tables 7 and 8 suggest that the Greece–Italy pair shares strong and persistent volatility and correlation dynamics, with no evidence of asymmetric responses. These findings imply a stable and robust transmission of volatility between the two markets, with

Italy playing a somewhat more reactive role in the short run.

4.3.2 Italy–Spain

Table 9: DCC(1,1) with GARCH(1,1) margins for Italy–Spain

Parameter	Estimate	Std. Error	t-value	p-value
μ_{IT}	0.000	0.001	0.000	1.000
ω_{IT}	0.000	0.000	0.581	0.561
$\alpha_{IT,1}$	0.225	0.047	4.780	0.000
$\beta_{IT,1}$	0.770	0.066	11.753	0.000
μ_{ES}	0.000	0.002	0.000	1.000
ω_{ES}	0.000	0.000	0.040	0.968
$\alpha_{ES,1}$	0.061	0.044	1.386	0.166
$\beta_{ES,1}$	0.926	0.060	15.564	0.000
$dcca_1$	0.000	0.005	0.035	0.972
$dccb_1$	0.999	0.034	29.099	0.000

Table 10: aDCC(1,1) with GARCH(1,1) margins for Italy–Spain

Parameter	Estimate	Std. Error	t-value	p-value
μ_{IT}	0.000	0.001	0.000	1.000
ω_{IT}	0.000	0.000	0.581	0.561
$\alpha_{IT,1}$	0.225	0.047	4.780	0.000
$\beta_{IT,1}$	0.770	0.066	11.753	0.000
μ_{ES}	0.000	0.002	0.000	1.000
ω_{ES}	0.000	0.000	0.040	0.968
$\alpha_{ES,1}$	0.061	0.044	1.386	0.166
$\beta_{ES,1}$	0.926	0.060	15.564	0.000
$dcca_1$	0.000	0.005	0.035	0.972
$dccb_1$	0.999	0.034	29.099	0.000
$dccg_1$	0.001	0.005	0.240	0.810

The DCC–GARCH(1,1) model for Italy and Spain in Table 9 reveals strong persistence in conditional volatility and highly stable correlations. For both markets, the β parameters are large and highly significant ($\beta_{IT} = 0.77^{***}$, $\beta_{ES} = 0.93^{***}$), showing that volatility shocks persist and cluster over time. Italy exhibits a significant ARCH effect ($\alpha_{IT} = 0.225^{***}$), while the Spanish ARCH coefficient is small and insignificant, confirming that Italian volatility is more reactive to new shocks whereas Spanish volatility is largely driven by long–run persistence.

The correlation dynamics are dominated by the persistence term ($dccb_1 = 0.999^{***}$), while the short–run correlation response is negligible ($dcca_1 = 0.000$). This implies that Italy–Spain conditional correlations evolve smoothly over time, without reacting strongly to recent innovations. The aDCC extension in Table 10 introduces the asymmetry term $dccg_1$, but the estimate is essentially zero and not significant. Hence, there is no evidence that negative shocks drive correlations differently than positive ones. Overall, the Italy–Spain pair is characterized by highly persistent volatility and correlation structures, with Italy reacting more to fresh shocks but no asymmetric effects in the correlation process.

4.3.3 Greece–Spain

Table 11: Cointegration vector for Greece–Spain (normalized on p^{GR})

Term	Estimate	Note
p^{GR}	1.000	fixed
p^{ES}	-0.920	from Johansen
c_0	-0.471	from Johansen

Table 12: VECM loadings (α) and short-run effects (Γ), Greece–Spain

Equation / Regressor	Estimate	Std. Error	t-value
Δp_t^{GR} **equation**			
ECT_{t-1}	-0.146	0.027	-5.395
Δp_{t-1}^{GR}	0.029	0.050	0.577
Δp_{t-1}^{ES}	0.369	0.089	4.142
Δp_t^{ES} **equation**			
ECT_{t-1}	0.001	0.014	0.105
Δp_{t-1}^{GR}	0.069	0.025	2.727
Δp_{t-1}^{ES}	0.505	0.045	11.209

As reported by VECM in equation **??**, Table 11 implies the long-run parity $p_{t-1}^{GR} - 0.920\, p_{t-1}^{ES} - 0.471 = 0$. Table 12 shows that Greece adjusts strongly and significantly towards this equilibrium (ECT loading -0.146, $t = -5.40$), while Spain's adjustment loading is near zero and insignificant. Short-run dynamics features sizable own and cross effects: Spanish returns are strongly persistent (Δp_{t-1}^{ES} in the ES equation,

Table 13: aDCC(1,1) with GARCH(1,1) margins for Greece–Spain (residuals of VECM)

Parameter	Estimate	Std. Error	t-value	p-value
μ_{GR}	-0.001	0.001	-0.296	0.595
ω_{GR}	0.000	0.000	2.417	0.016
$\alpha_{GR,1}$	0.496	0.298	1.667	0.096
$\beta_{GR,1}$	0.480	0.077	6.246	0.000
μ_{ES}	0.000	0.001	0.624	0.533
ω_{ES}	0.000	0.000	2.984	0.003
$\alpha_{ES,1}$	0.186	0.095	1.953	0.051
$\beta_{ES,1}$	0.560	0.103	5.421	0.000
$dcca_1$	0.150	0.076	1.989	0.047
$dccb_1$	0.467	0.122	3.818	0.000
$dccg_1$	0.360	0.210	1.712	0.087

$t \approx 11.21$), and both equations display significant cross-market impacts at lag one (e.g., Δp_{t-1}^{ES} in the GR equation, $t \approx 4.14$; Δp_{t-1}^{GR} in the ES equation, $t \approx 2.73$). Overall, Greece bears the burden of error correction, while Spain leads short-run movements.

Turning to volatility and correlation structure, Table 13 documents persistent conditional variances in both markets (large and highly significant β's), with Italy-style strong ARCH more evident for Spain ($\alpha_{ES,1} \approx 0.19$, $p \approx 0.051$) and a somewhat weaker, marginally significant ARCH component for Greece. The correlation dynamics are persistent and reactive: $dccb_1 \approx 0.47$ is highly significant and $dcca_1 \approx 0.15$ is borderline significant, indicating that correlations both retain memory and respond to new standardized shocks. The asymmetry parameter $dccg_1$ is only marginally significant at the 10% level, offering at best weak evidence that negative shocks alter correlations differently from positive shocks. In sum, the Greece-Spain pair is cointegrated with adjustment concentrated in Greece, and its joint volatility exhibits clustering with moderately persistent, time-varying correlations.

5 Discussion

The empirical findings of the present study reveal that the volatility of Italian prices exhibits a stronger response to recent innovations, whereas the corresponding term

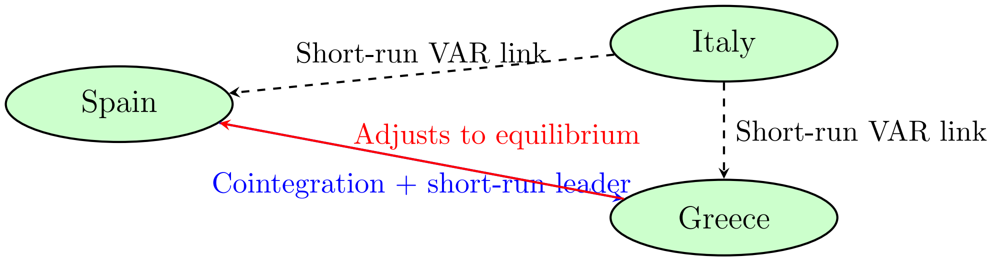

Figure 2: Dynamics among olive oil markets (Greece, Italy, Spain). Blue = cointegration, red = adjustment, black dashed = short-run VAR.

for Greece is not significant. This asymmetry in responses suggests that the Italian market is more sensitive to contemporaneous shocks, whereas Greek volatility is mainly driven by its past. The aforementioned findings of asymmetric responses are in agreement with the studies of Emmanoulides et al. (2014) and Panagiotou and Stavrakoudis (2023). Additionally, the results indicate that Italy plays a more reactive role in the short run. Here are some of the reasons of why Italy is more sensitive to short-run shocks:

1. Financialization and Speculation: Italy is the world's largest exporter of olive oil by value. Its market is deeply tied to financial markets. Prices are set on commodity exchanges (such as the Mercato dei Derivati di Borsa Italiana), and vast quantities are traded in futures and other derivative contracts. Traders and speculators react immediately to news (a shock), buying or selling contracts based on expectations of future scarcity or surplus. This amplifies the impact of any contemporaneous shock.

2. Global Hub and Re-Exporter: Italy is not only a major producer, but also EU's largest olive oil importer. It imports bulk oil from Spain, Tunisia, Greece, and other countries, blends it, bottles it, and re-exports it under Italian brands. This makes its market incredibly sensitive to supply shocks anywhere in the Mediterranean. A drought announcement in Spain, a tariff change in Tunisia, or a logistics disruption at a major port (like Genoa) is a contemporaneous shock that immediately affects Italian prices and volatility.

3. Brand Sensitivity and Consumer Sentiment: The value of Italian olive oil is heavily tied to its premium branding ("Made in Italy," PDO/PGI certifica-

tions). A contemporaneous shock, such as a food safety scandal (e.g., an "extra virgin" fraud investigation), a negative international press report, or a sudden shift in global consumer demand (e.g., a key importing country imposing a tariff), will cause immediate volatility as brands scramble to protect their reputation and market share.

4. High Integration with Global Markets: The Italian market is a price setter for the world. It constantly receives and processes information from global supply chains, currency markets (EUR/USD fluctuations affect export competitiveness), and international demand. This constant flow of information creates a market that is perpetually reacting to the "now."

Greece's olive oil market is more traditional, localized, and dominated by a vast number of small-scale producers. Its behavior is more inertial, meaning that today's volatility is primarily a function of yesterday's. Below are some of the reasons why Greek volatility is mainly driven by its past:

1. Dominance of Small-Scale Production and "Social Crop": A considerable proportion of Greek olive oil is produced by hundreds of thousands of smallholder families (often with only a few trees). For them, olive oil is not just a commodity; it is a cultural staple and a form of savings. This leads to strong behavioral inertia.

2. Holding Behavior: Farmers tend to hold onto their oil, releasing it to the market gradually based on personal financial needs rather than reacting immediately to price shocks. This creates a delayed response to market conditions.

3. Past Volatility Creates Expectations: If last year was volatile (e.g. prices spiked due to a poor harvest), farmers this year will be hesitant to sell, anticipating similar price movements. This past experience directly drives current decision-making and therefore current volatility.

4. Less Financialized and More Localized Market: The Greek market is by far less involved in futures trading and financial speculation compared to Italy's. Direct transactions between producers and local mills or cooperatives more often

determine prices. This lack of a high-frequency financial market layer dampens the immediate impact of contemporaneous shocks. The market moves more slowly, with momentum.

5. Higher Domestic Consumption and Inelastic Supply: Greeks have the highest per capita consumption of olive oil in the world. A significant portion of production is consumed domestically or by the extended family network. This creates a relatively inelastic supply. Even if there is a price shock (e.g., a sudden surge in international demand), many small producers are either unable or unwilling to immediately increase their market supply. The system's reaction is slow and based on past patterns.

6. Climatic and Harvest-Driven Momentum: Greece's production is more susceptible to intense biennial bearing cycles (alternating high and low-yield years). A past year of low output (high volatility) strongly predicts a recovery year, and vice versa. This biological and climatic momentum is a powerful autoregressive force. The memory of the size and quality of the past harvest is the single most significant factor for the current season.

According to the empirical results of this work, the prices of Greek and Spanish olive oil move together in a long-run equilibrium relationship. If they drift apart, the Greek price does most of the adjusting to restore the equilibrium, while the Spanish price acts as the "leader" or anchor. These findings are in agreement with the study by Theofanous and Tremma (2024) in which Spain is the central market. The reasons might be:

1. Spain as the Dominant Price Setter: Spain is the undisputed giant of olive oil production, accounting for 35% of global supply in an average year and has massive industrialized farms. This volume gives Spain tremendous pricing power. The Spanish price, particularly from key regions such as Jaén, becomes the de facto global benchmark price. Greece, as a smaller producer (7% of global supply), is a price taker relative to Spain.

2. The Role of Italy as a Conduit: A massive amount of Greek olive oil is exported in bulk to Italy. Italian blenders and bottlers use it to mix it with oils of other origins. Therefore, the price that Italian buyers are willing to pay for Greek oil is directly influenced by the price of Spanish oil (their main alternative). If Spanish prices fall, Italian buyers will immediately offer less for Greek oil, forcing the Greek price to fall to maintain its competitive position. This mechanism forces Greece to adjust to Spain's price level.

3. Market Size and Liquidity: The Spanish market is deeper and more liquid. Large price movements in Spain, due to a harvest shock or increased export demand, are transmitted almost instantly to the global market. The smaller and more fragmented Greek market must then react and align itself with this new global price level, doing the "adjusting" in the cointegrating relationship.

4. Quality Perception & Branding: Although, both produce high-quality oil, Spain has been more successful in building a consistent global brand for its bulk and bottled oil. This brand power allows it to command a more stable price premium, making its price the stronger anchor in the relationship.

In addition, periods of high volatility (characterized by large price swings) are often followed by further periods of high volatility, and periods of calm are typically followed by more calm. This is a near-universal feature of agricultural commodity prices.

The reasons that might be common to both countries are:

1) Weather Shocks: Olive oil is an agricultural product. A drought, frost, or heat wave in either country does not last a single day; it affects the entire growing season. A weather shock in Spain (e.g. the 2023 drought) creates a prolonged period of uncertainty about the final harvest size, causing sustained high volatility. The same is true for Greece.

2) Sequential Information Flow: Information arrives in clusters. During the growing season (Spring-Summer), forecasts about the harvest are updated continuously. A poor forecast leads to several weeks or months of volatile price adjustments as the market digests the information.

3) Speculative Trading: In times of expected shortage, speculative traders enter the market, amplifying price moves on both the upside and the downside. This speculative activity tends to occur in bursts, creating volatility clusters.

6 Conclusions

This study presents a comparative analysis of olive oil producer prices in Greece, Spain, and Italy, the European Union's three largest olive oil-producing countries, yielding a clear picture of how these markets interact in both the long and short run. The findings reveal that the three major EU markets cannot be treated as a single well-integrated market, a finding that aligns with previous research (see Section 1). The analysis indicates a complex and asymmetric market structure, where Spain acts as the primary price setter, Italy functions as a conduit for short-term volatility, and Greece is primarily a price taker that adjusts to long-run trends set by Spain.

Employing Johansen's cointegration analysis alongside a DCC-GARCH framework, the study aimed to uncover the long-run equilibrium relationships and short-run volatility spillovers that define this critical olive oil producer triangle.

By analyzing the relations among Greece, Italy, and Spain in pairs, we found that cointegration is present only for the pair Greece-Spain. Greece adjusts back to the long-run parity (ECT ≈ -0.146, t≈ -5.4) while Spain leads short-run returns; Correlations are persistent but not extreme, and asymmetry is at most marginal.

No cointegration is found for the Greece/Italy pair; a VAR in differences captures short-run spillovers. The correlations are very stable, with no asymmetric response, and Italy is the most shock-sensitive market in terms of volatility. No long–run link emerges for the Italy/Spain pair; we have observed short–run dynamics. Volatility clustering is pronounced, with Italy more reactive to new shocks, while the correlations are persistence–dominated and symmetric.

Across all three markets, prices are I(1). The single long–run relation is Greece–Spain; Spain anchors short–run mean dynamics, whereas Italy transmits volatility more aggressively. Correlations are highly persistent and largely symmetric; evidence of correlation asymmetry is weak.

These findings have significant implications for policymakers at the EU level, particularly in an era of increased price volatility linked to climate change and geopolitical events. At the EU level, policymakers could recognize Spain's role as the primary price leader and Italy's role as a highly reactive global hub—importing bulk oil for blending and re-exporting. The analysis showed that production shocks within Spain (i.e, a severe drought) will inevitably have spill-over effects, impacting other countries, especially Greece. EU-level policies aiming at market stabilization must, therefore, recognize Spain's systemic importance. In addition, Italy's role as a conduit for short-term volatility makes it a critical channel for shocks transmission throughout the Mediterranean. Understanding this dynamic is crucial for formulating policies to mitigate extreme price events and to improve food security in the EU.

The present work has certain limitations. First, the analysis has been limited to the three largest EU producers. Portugal was excluded due to an insufficient number of data observations. Second, other non-EU Mediterranean countries, like Tunisia, a major supplier to Italy, is not included in the model.

Future research could include additional key Mediterranean players like Portugal (if data becomes available) and Tunisia or even Turkey, to create a more complete picture of regional price dynamics. Another interesting extension of the research could be to incorporate other variables into volatility models, such as climate data or harvest forecasts, to better explain the sources of shocks that drive the market. This extension could offer deeper insights into the sources of market shocks. Also, in the future, as more data becomes available, it would be possible to include dynamic correlations in the model. Finally, this study only examined extra virgin olive oil. Different grades of olive oil, such as virgin or lampante, could also be investigated.

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