Price dependence among the major EU extra virgin olive oil markets: A time scale analysis

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September 2021

Abstract

The goal of this study is to assess the strength and mode of price dependence by time scale, among the extra virgin olive oil markets of Italy, Spain and Greece. These three Mediterranean countries are responsible for 95% of olive oil production within the European Union and they account for more than 50% of the olive oil exports worldwide. For the empirical analysis, monthly prices from the aforementioned countries are utilized along with the tools of discrete wavelets and nonparametric copulas. Results indicate that: (a) Price linkages in the short-run are significantly different from those in the longer-run, with price dependence being stronger in the longer-run, and (b) in the very long run, price shocks of the same sign but of different magnitude are transmitted from Italy to Spain with a higher probability than they are 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 finding of asymmetric co-movement is not consistent with well-integrated markets.

Keywords: Wavelets; Copulas; Extra virgin olive oil; Price dependence.

JEL classification: C14, Q13, L66

1 Introduction

Market integration of geographically separated markets has been a subject of great importance for economists as well as for policy makers. Integration is a prerequisite for economic efficiency, namely the maximization of benefits accruing to the society from the existence and the efficient operation of markets (Fousekis and Grigoriadis, 2019). Well functioning integrated spatial markets are characterized by strong price dependence, meaning that price shocks in one market induce price responses to the other.

The European Union (EU), as a prime example, has been engaged in a process of market integration for a very long period of time. Starting in 1993, with the Single Market Programme (SMP), all tariff and non-tariff barriers between the geographically separated markets of the member states within the EU were removed.[1] The main idea behind the SMP was to promote trade and create a more efficient market. As a consequence, over the last twenty-five years, there has been a number of empirical studies on the integration of the (especially food) markets among the member states of the EU (Zanias, 1993; Morgan and Wakelin, 1999; Emmanouilides and Fousekis, 2015a, 2012; Serra et al., 2006; Fousekis and Grigoriadis, 2019; Sanjuán and Gil, 2001). The aforementioned empirical research on the integration of the EU food markets has been undertaken with a variety of statistical tools and econometric techniques. More specifically, the linear co-integration analysis was employed by Zanias (1993) as well as by Sanjuán and Gil (2001). Non-linear co-integration techniques were employed by Emmanouilides and Fousekis (2012) and by Emmanouilides and Fousekis (2015a). Parametric and non-parametric regressions were employed by Serra et al. (2006). Lastly, the statistical tool of copulas was utilized by the studies of Emmanoulides et al. (2014) and by Grigoriadis et al. (2016). In the majority of the studies, the empirical findings indicate that markets are well integrated. On the other hand, there are some works that suggest a low degree of integration (C. Emmanoulides, P. Fousekis, and V. Grigoriadis, 2014, found a low degree of integration in the short-run) or no integration (Zanias, 1993) among the food markets

[1]The Single Market Programme was adopted in 1985 and was fully implemented by 1993.

examined.

In the last decade, copulas have gained momentum in the analysis of co-movement between stochastic processes (Reboredo, 2011, 2012; Emmanouilides and Fousekis, 2015a; Panagiotou and Stavrakoudis, 2016; Emmanoulides et al., 2014; Goodwin and Hungerford, 2015; Neumeyer et al., 2019; BenSaïda, 2018; García-Gómez et al., 2020; Gaupp et al., 2017; Sriboonchitta et al., 2013). The most attractive feature of the copulas is that they can deal with non-linearities, asymmetries and heavy tails of the marginal and the joint distributions of variables. In addition, copulas allow for the joint behavior of random processes to be modelled independently of their marginal distributions. The latter presents significant flexibility in empirical works (Panagiotou and Stavrakoudis, 2016; Emmanouilides and Fousekis, 2015b; Goodwin and Hungerford, 2015; Fousekis et al., 2017).

On the other hand, a noticeable disadvantage of the copulas as well as of the commonly used approaches, is that they do not account for the role of time scale (time horizon) in price dependency. The latter means that some agents operate on short time scales/horizons, some on medium time scales and some others operate on much longer planning time horizons. As noted by Fousekis and Grigoriadis (2016b), differences in agents' time horizons may render the relationships between economic time series scale and frequency dependent. Scale and frequency are inversely related: a high scale is related with low frequency whereas a low scale is related with a high frequency. Accordingly, when it comes to spatial market integration, scale/frequency dependence suggest that the strength and the mode of price linkages may differ by time scale and time frequency.

In the most recent study, Emmanouilides and Proskynitopoulos (2019) analyze the spatial price causality structure between the pig meat markets of 24 European countries. More specifically, the authors studied the EU pig meat market as a dynamic complex network of linkages between prices in member states. The study investigated the temporal development of the spatial network of price relationships, and through the dynamics of its major structural characteristics we draw insights about the horizontal agricultural market integration process in the EU. For the empirical part, weekly time-series data from 2007 to 2018 were utilized along with non-linear Granger causality. The data provide evidence not only for a large degree of heterogeneity in market power between countries, but also for the existence of market segregation into high and low power groups (clubs) that are strongly connected to each other. The presence of such groups is an inefficiency of the market system in the European Union.

In the light of the preceding, the goal of this study is to analyze the strength and the pattern of price dependence among the major extra virgin olive oil markets in the EU, namely Italy, Spain and Greece. These three Mediterranean countries are responsible for 95% of olive oil production within the EU (European Commission, 2020a). Concurrently, more than 70% of the world olive oil production stems from the EU (European Commission, 2020b). On the consumption side, Italy, Spain and Greece account for 80% of olive oil consumption within the EU (European Commission, 2020a). Statistics regarding olive oil intra-trade among Italy, Spain and Greece are also very remarkable. More specifically, above 70% of Spain's exports and almost 90% of Greek exports have Italy as their destination; 98% of Italy's imports from EU members stem from Spain and Greece (European Commission, 2020b). The exports of Spain and Greece to Italy consist to a large degree of extra virgin and virgin olive oil (European Commission, 2020a).

In the present work, the evaluation of price dependence is undertaken with the employment of discrete wavelets along with copulas, while utilizing monthly prices of extra virgin olive oil from Italy, Spain and Greece. More specifically, the tool of discrete wavelets is applied initially to analyse the activity of the individual time series into different components where each component is associated with a time scale (Fousekis and Grigoriadis, 2016a,b). Afterwards, the tool of non-parametric copulas is employed to extract information about dependence by scale/frequency level.

The present manuscript builds on the work by Emmanoulides et al. (2014). The aforementioned study, assesses the degree and the structure of price dependence in the principal EU extra virgin olive oil markets (Spain, Italy and Greece), with the utilization of the statistical tool of parametric copulas and monthly data. On average, the empirical results reveal olive oil prices are likely to boom together but not to crash together. The present study builds on the study by Emmanoulides et al. (2014) since it utilizes monthly extra virgin olive oil data in order to also assess the degree and the structure of price dependence Spain, Italy and Greece. However it departs from the seminal study in two ways: First of all, with the utilization of discrete wavelets, data are divided the assessment of price dependence has been undertaken for low, medium and high frequencies, namely time scales. Secondly, the degree and the structure of price dependence, for the different time scales, has been estimated with the use of nonparametric copulas. As Fousekis and Grigoriadis (2016a) point out, the non-parametric estimation of copulas allows the data "to speak for themselves", eliminating this way potential misspecification bias.

The combination of the statistical tools of discrete wavelets and nonparametric copulas, enables us to determine the extent to which the mode and the strength of price linkages change by the time horizon (i.e. short-, medium-, and longer-run). The work by Fousekis and Grigoriadis (2016b) on the to investigation of price dependence in the international butter markets, has been (so far) the only earlier study that has employed both wavelets and copulas for agricultural/dairy commodities. The authors used monthly wholesale prices from Oceania and the European Union and the statistical tools of copulas and wavelets. Their empirical results suggested that price linkages between the two butter-producing regions are weak in the short-run but stronger in the long-run. Furthermore, the time scale was relevant not only for the intensity but for the structure of price co-movement between Oceania and the EU. More specifically, in the long run, strong positive shocks were transmitted with a higher intensity compared to strong negative ones, indicating asymmetric price dependence.

In what follows, Section 2 presents the methodology for copulas and wavelets, Section 3 the data and Section 4 the empirical analysis, the results and discussion. Section 5 offers conclusions.

2 Methodological framework

2.1 Discrete wavelets

As documented in the literature, financial time series data tend to demonstrate high non-normality, for instance, skewness, leptokurtosis and volatility clustering, particularly in the case of high-frequency data (Engle, 1982; Andersen et al., 2001; Lambert and Laurent, 2001). Different frequencies are associated with different time scales. An appealing feature of the wavelet method is that it transforms the original time series into different frequency components and the resolution is matched to its scale (Gençay et al., 2001; Percival and Walden, 2000; Reboredo and Rivera-Castro, 2014). The fundamental idea behind wavelets is to analyze according to scale.

Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. Wavelet algorithms process data at different scales or resolutions. Wavelets are well-suited for approximating data with sharp discontinuities.

Wavelet is a well-established technique that decomposes a time series into small waves that begin at a specific point in time and end at a later specific point in time. A significant advantage of this approach is that frequency information can be obtained without losing the timescale dimension. Another advantage of wavelet analysis is that it does not need to assume anything about the data generating process for the return series under investigation (Gençay et al., 2001; Ramsey, 2002).

We can obtain a discrete wavelet transform (DWT) through discretizing the continuous variables a and b on the right hand side of equation (1) (Gencay et al 2001, p. 103).

$$r(t) = 1/C_\psi \int_0^\infty \int_{-\infty}^\infty (1/a^2) D(a,b) \psi_{a,b}(t) dbda \tag{1}$$

where r(t) stands for the wavelet transformation, C_ψ represents the abstract admissibility condition, D(a,b) is a function of a and b, and $\psi_{a,b}(t)$ is the wavelet basis function.

Let $a = 2^{-j}$,$b = k2^{-j}$, j = 1,...,J. Then, r(t) $\in$ L2(R) can be represented by the following expansion:

$$r(t) = \sum_{k\in Z} S_{J,k}\, F_{J,k}(t) + \sum_{k\in Z} d_{J,k}\, C_{J,k}(t) + .. + \sum_{k\in Z} d_{j,k}\, C_{j,k}(t) + \sum_{k\in Z} d_{1,k}\, C_{1,k}(t) \quad (2)$$

where J is a positive integer that denotes the number of multi-resolution scales and k is a translation parameter. Equation (2) is the multiresolution decomposition of the signal. The definition of $F_{J,k}(t)$ and $C_{j,k}(t)$ are given by:

$$F_{J,k}(t) = 2^{J/2}\, F(2^J t - k) \quad (3)$$

$$C_{j,k}(t) = 2^{j/2}\, C(2^j t - k) \quad (4)$$

The so-called father wavelet $F_{J},_{k}$ and mother wavelet $C_{j},_{k}$ satisfy the following conditions:

$$< F_{J,k}(t), F_{J,k'}(t) >= \int_{-\infty}^{\infty} F_{J,k}(t)\, F_{J,k'}(t)dt = G_{k,k'} \quad (5)$$

$$< C_{j,k}(t), F_{J,k'}(t) >= \int_{-\infty}^{\infty} C_{j,k}(t)\, F_{J,k'}(t)dt = 0 \quad (6)$$

$$< C_{j,k}(t), C_{j',k'}(t) >= \int_{-\infty}^{\infty} C_{j,k}(t)\, C_{j',k'}(t)dt = G_{j,j'}\, G_{k,k'} \quad (7)$$

where Gm,n = 1 if m = n, Gm,n = 0 if $m \neq n$, and $< \cdot,\cdot >$ is the inner product. Similar to the continuous transform, the wavelet is controlled by two parameters: time and frequency. The translation parameter k indicates the location and the non-zero proportion of the wavelets, where as the length of the wavelet is reflected by j, which is a scalar factor. The scaling coefficients

$$S_{J,k} = \int F_{J,k}(t)\, r(t)dt \quad (8)$$

based on the father wavelet represent the soft components of the original data at the coarsest scale. Meanwhile, the wavelet coefficients

$$d_{j,k} \quad = \quad \int C_{j,k}(t)\, r(t) dt \tag{9}$$

based on the mother wavelet are used to capture the details of the high-frequency components of the original data. If all the integer translations are substituted by a sequence of dyadic scales, and let $a = 2^{-j}$ and $b = k2^{-j}$, then we obtain the maximal overlap discrete wavelet transform (MODWT). As documented in Percival and Mofjeld (1997), Percival (1995) and Gençay et al. (2001), MODWT refers to some flexible properties that the DWT does not possess. MODWT does not have any restriction on the data size T, whereas the j-th order partial of DWT imposes a restriction on the data size: T has to be a multiple of 2^j. The wavelet coefficients and scaling coefficients of a MODWT multiresolution analysis linking with zero-phase filters indicate that the location of events in the original data cannot be changed. We can take advantage of this information and encode the wavelet coefficients with a bit rate that produces minimal subjective distortions. Another advantage of MODWT is that it provides an asymptotically more efficient variance estimator than simple DWT. Furthermore, the pattern of wavelet coefficients and scaling coefficients is not changed by a shift in the original time series because the MODWT is translation invariant.

2.2 Local and global dependence with the use of copulas

Copulas have realized widespread application in empirical models of joint probability distributions (see Nelsen (2007); Joe (2014) for more details). The aforementioned models use a copula function to tie together two marginal probability functions that may or may not be related to one another. A two–dimensional copula, $C(u_1, u_2)$, is a multivariate distribution function in the unit hypercube $[0, 1]^2$ with uniform U(0,1) marginal distributions. As long as the marginal distributions are continuous, a unique copula is associated with the joint distribution, H, and is described in equation (10). This function constitutes a form of the principal result of copula theory (Sklar's theorem). It is obtained as:

$$C(u_1, u_2) = H(H_1^{-1}(u_1), H_2^{-1}(u_2)) \tag{10}$$

Given a two-dimensional copula, $C(u_1, u_2)$, and two univariate distributions, $H_1(x)$ and $H_2(y)$, equation (10) is a two-variate distribution function with marginals $H_1(x)$ and $H_2(y)$, whose corresponding density function can be written as:

$$h(x, y) = c(H_1(x), H_2(y))h_1(x)h_2(y), \tag{11}$$

where the functions h_1 and h_2 are the marginal distribution density function of the distribution functions H_1 and H_2 respectively. In addition x,y are stochastic processes and u_1 and u_2 are related to x,y.

There are two types of dependence measures: i) global dependence measures provide information about the strength of dependence between stochastic processes over all their support, and ii) local dependence measures provide information about the intensity of dependence over different subsets of the support. Both dependence measures (local and global) are invariant to strictly increasing transformations of the processes that they describe. Such transformations are the functions of the ranks of the underlying marginal distributions.

The most common employed rank-based measure of global dependence is Spearman's rho (ρ). The aforementioned measure can be expressed with the use of the following copula distribution function:

$$\rho = 12 \int_0^1 \int_0^1 C(u_1, u_2)\, \mathrm{d}u_1 \mathrm{d}u_2 - 3, \tag{12}$$

(Schweizer and Wolff, 1981). Spearman's rho (ρ) is useful for summarizing the strength of dependence on average.[2] However, the intensity of dependence might differ for the various subsets of the support. Richer insights about the relationships under study may be, therefore, obtained from assessing local dependence. The relevant notions for that are the quantile dependence coefficients.

[2] Spearman's rho (ρ) assumes values between -1 and 1.

Another rank based test of functional dependence is Kendall's τ. It is calculated from the number of concordant (P_N) and disconcordant (Q_N) pairs of observations in the following way:

$$\tau_N = \frac{P_N - Q_N}{\binom{N}{2}} = \frac{4P_N}{N(N-1)} - 1, \tag{13}$$

If a copula function (C) is known then τ can be calculated as:

$$\tau = 1 - 4 \int\int_{[0,1]^2} \frac{\partial C}{\partial u_1} \frac{\partial C}{\partial u_2} \, \mathrm{d}u_1 \, \mathrm{d}u_2 \tag{14}$$

Equations (15) and (16) present the quantile dependence coefficients. Tail dependence coefficients, denoted with λ, are limits of the former. Accordingly, tail (extreme) co-movement is measured by the upper, λ_U, and the lower, λ_L, dependence coefficients, such that λ_U, $\lambda_L \in [0,1]$, which are defined as

$$\lambda_U^q = \Pr(u_2 > q | u_1 > q) = \frac{1 - 2q + C(q,q)}{1-q}, \quad 1/2 < q < 1 \tag{15}$$

$$\lambda_L^q = \Pr(u_2 \leq q | u_1 \leq q) = \frac{C(q,q)}{q}, \quad 0 < q \leq 1/2. \tag{16}$$

Equation (15) defines a set of upper quantile dependence coefficients providing the conditional probability that the random process u_2 receives a value strictly higher than its q quantile given that the random process u_1 receives a value strictly higher than its q quantile, as well (Fousekis and Grigoriadis, 2016b) Equation (16) defines a set of lower quantile dependence coefficients providing the conditional probability that the random process u_2 receives a value at most equal to its q quantile given that the random process u_1 receives a value at most equal to its q quantile, as well. By varying q one may trace out how the intensity of dependence behaves at the different parts of the support.

3 Data

The data for the empirical application are monthly extra virgin olive oil prices (measured in euros per 100 kilograms) from Italy, Spain, and Greece. The time period of interest is January 2000 to March 2020. Data were obtained from the European Commission (2020c). Figure 1 presents the evolution of prices of the extra virgin olive oil for the aforementioned countries.[3]

Worldwide, olive oil production averages 2.7 million tons. The European Union (EU) is the major producer of olive oil in the world. The EU accounts for about 75% of the world production of olive oil. Spain with 60%, Italy with 21% and Greece with 14% account for about 95% of the EU production. Spain is also the leading olive oil producer in the world; 35% of the total olive oil production in Spain is extra virgin. Italy comes in second place worldwide; 60% of the production in Italy is extra virgin olive oil (European Commission, 2020a). Greece holds third place; it produces approximately 350,000 tons of olive oil annually, of which more than 80% is extra virgin. The exports of Spain and Greece to Italy consist to a large degree of extra virgin and virgin olive oil, sold in bulk. These exports are bottled and/or blended by a small number of major Italian companies and are distributed worldwide (Emmanoulides et al., 2014; Panagiotou, 2015). Especially for the case of Greece, nearly half of the annual olive oil production is exported but only some 5% of this reflects the origin of the bottled product. Trade flows between Spain and Greece are insignificant when compared with those of the two countries with Italy. It is worth mentioning that although Italy is a deficit market within the EU, it is one of the biggest olive oil exporters in the world, with a share of about 30%. Spain's share worldwide is approximately 20% (Panagiotou, 2015).

With regard to consumption patterns, Italy and Greece consume primarily extra virgin olive oil, whereas consumption of extra virgin olive oil in Spain represents almost 50% of the total olive oil domestic consumption (European Commission,

[3] 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 oleic acid per 100 grams of oil.

2020b). European Union is the world's biggest consumer of olive oil, with a share close to 70%. Spain, Italy, and Greece account for about 80% of the EU's consumption (Emmanoulides et al., 2014; Panagiotou, 2015).

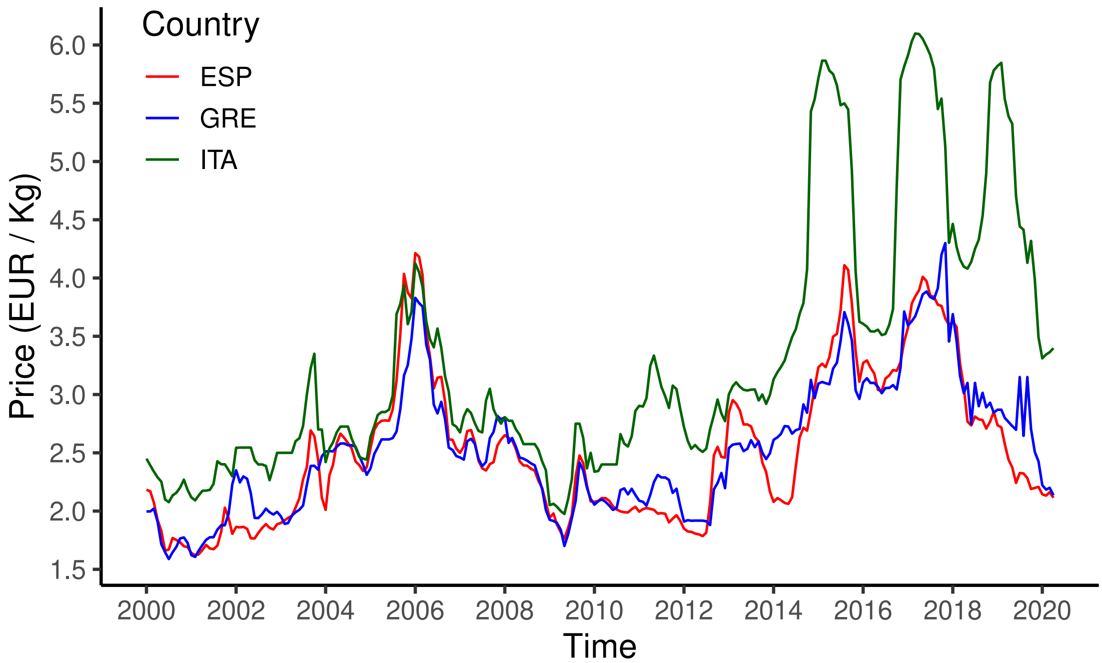

Figure 1: Time series of extra virgin olive oil prices.

Following the relevant literature, that have employed wavelets along with copulas in order to empirically investigate time series (Reboredo and Rivera-Castro, 2014; Fousekis and Grigoriadis, 2016b), the present paper utilizes the rates of price change (raw price shocks), calculated as $dlnP_{it}$, where P_{it} is the price of extra virgin olive oil in market i = Italy, Spain and Greece at time t. Figure 8, in the section of the Appendix, presents the logarithmic returns of the extra virgin olive oil prices for Spain, Greece and Italy.

In order to obtain the copula data which is required for the empirical analysis of the study, we follow the semi-parametric approach proposed by Chen and Fan (2006). The approach involves three steps:

1. Due to the fact that the rates of price change may exhibit autocorrelation and ARCH effects, the data are filtered: a skewed-t-ARMA–GARCH model is fitted to the raw price shocks for each of the series. Accordingly, Table 1 presents

the p-values resulting from the application of the Lung-Box and the auto-regressive conditional heteroskedasticity Lagrange multiplier (ARCH–LM) tests to the filtered data at various lag lengths. Lag order is indicated in parenthesis. Normality of residuals has been tested with Kolmogorov-Smirnov and Cramer von Mises tests. In all cases both tests rejected normality with p-value < 0.001. Results in Table 1 indicate that the filtered data are free from autocorrelation and from ARCH effects.

2. The obtained residuals are standardized (filtered data), creating this way the copula data on (0,1). Copula data are then used to calculate the respective empirical distribution functions.

3. The estimation of copula models is conducted by applying the maximum likelihood (ML) estimator to the copula data (Canonical ML).

Table 1: Residual diagnostics from ARMA-GARCH precedure.

	ESP	GRE	ITA
mean	-0.0015	-0.0032	-0.0042
variance	0.0019	0.0027	0.0030
kurtosis	4.5278	6.1279	8.2679
skewness	0.5134	-0.1412	0.5884
KS	0.0008	<0.0001	<0.0001
CvM	<0.0001	<0.0001	<0.0001
LB(1)	0.3544	0.4512	0.7246
LB(5)	0.1456	1.0000	0.9996
LB(9)	0.1123	0.9978	0.6421
AR(3)	0.4222	0.6146	0.7855
AR(5)	0.1872	0.6463	0.7210
AR(7)	0.1435	0.7241	0.7904

Lastly, random processes can be influenced by the presence of extreme market conditions. Thus, before selecting the appropriate functional form for a copula, we need to test for time–varying dependence. If the copula parameters are constant over the period of time examined in this study, then the empirical copula is derived non-parametrically directly from the data. On the other hand, if the parameters are influenced by breaks and/or persistent shifts, then it is possible that more than one copula families might be selected in order to describe the nature of price dependence between the two market levels. Copula stability was tested with the employment of Busetti and Harvey (2011) test. Table 2 presents the values of the constancy test for the three quantiles of the bivariate empirical copulas (0.25, 0.5 and 0.75) for each one of the three pairs. Under the null hypothesis of stationarity, the quantile (τ) of the bivariate empirical copula is constant. The values of the statistics are in all cases below the 5 per cent critical value (0.461), suggesting that the null hypothesis of constancy cannot be rejected. Hence, there is not sufficient statistical evidence for breaks and/or persistent shifts in the empirical copulas examined in this study.

Table 2: Busetti-Harvey test statistics.

	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$
ESP/GRE	0.125	0.095	0.077
ESP/ITA	0.055	0.128	0.079
GRE/ITA	0.072	0.301	0.047

Critical values are 0.743, 0.461 and 0.347 for the 1, 5 and 10% levels of significance, respectively.

All computations in this study have been carried out with R (version 4.0.3, R Core Team (2014)).

4 Empirical models, results and discussion

4.1 Empirical models

In the first step of the empirical analysis, all three time series are filtered through wavelet transform technique in order to decompose them into time scale components. Wavelets analysis does not need any stationary assumptions in order to decompose the time series. Accordingly, the Maximal-Overlap DWT, a modified version of the DWT, has been applied to the standardized innovations. The compact Daubechies least asymmetric wavelet filter of length 8 (LA(8)) has been employed in the present study. The latter is the most commonly used in economic applications (Fousekis and Grigoriadis, 2016b; Reboredo and Rivera-Castro, 2014).

With 243 observations available, the maximum decomposition level J, given by $log_2(T)$, equals to 8. However, following the practice of earlier works (Crowley and Hallett, 2014), and in order to make qualitative inferences about the time period (short-run, medium-run and longer-run), the maximum decomposition level J has been set equal to three. The first detail (D1) represents activity taking place within a period of 2 to 4 months (very short- and short-run dynamics), the second detail (D2) represents activity taking place between 4 and 8 months and the third detail (D3) represents activity taking place between 8 and 16 months. Lastly, the smooth (S3) represents activity taking place beyond 16 months (longer-run dynamics). The MRD has been implemented using the waveslim package in R (Whitcher, 2022).

Figures 2, 3 and 4 present the details and the smooths produced from the application of the MRD to the filtered rates of price shocks in Spain (ESP), Greece (GRE) and Italy (ITA), respectively. As one can observe, for every country, for shorter time periods, the price changes are more volatile, but as we move to longer time periods, price changes are smoother.

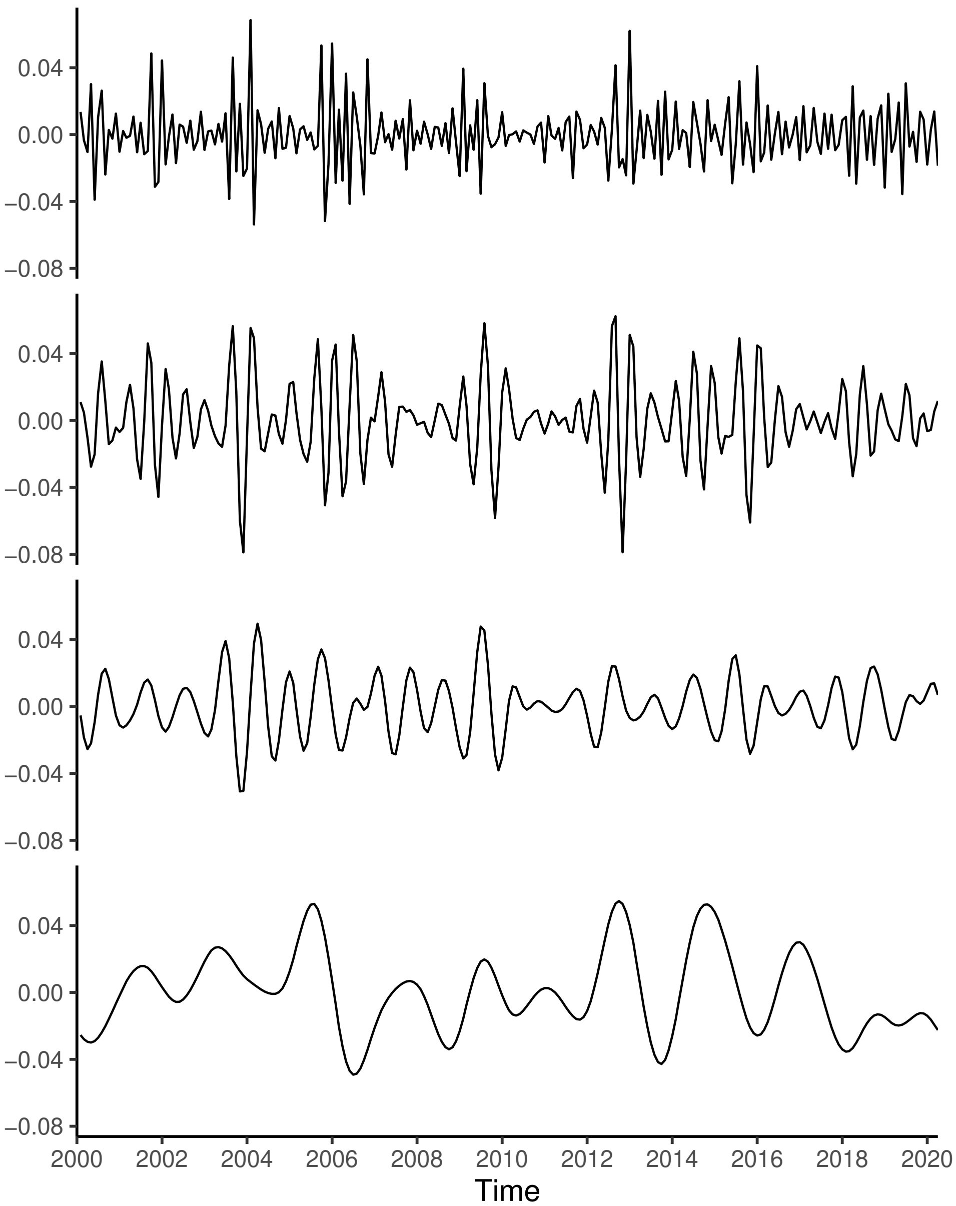

Figure 2: Wavelets of ESP: from top to bottom we have D1, D2, D3 (the three details) and S3 (the smooth), respectively.

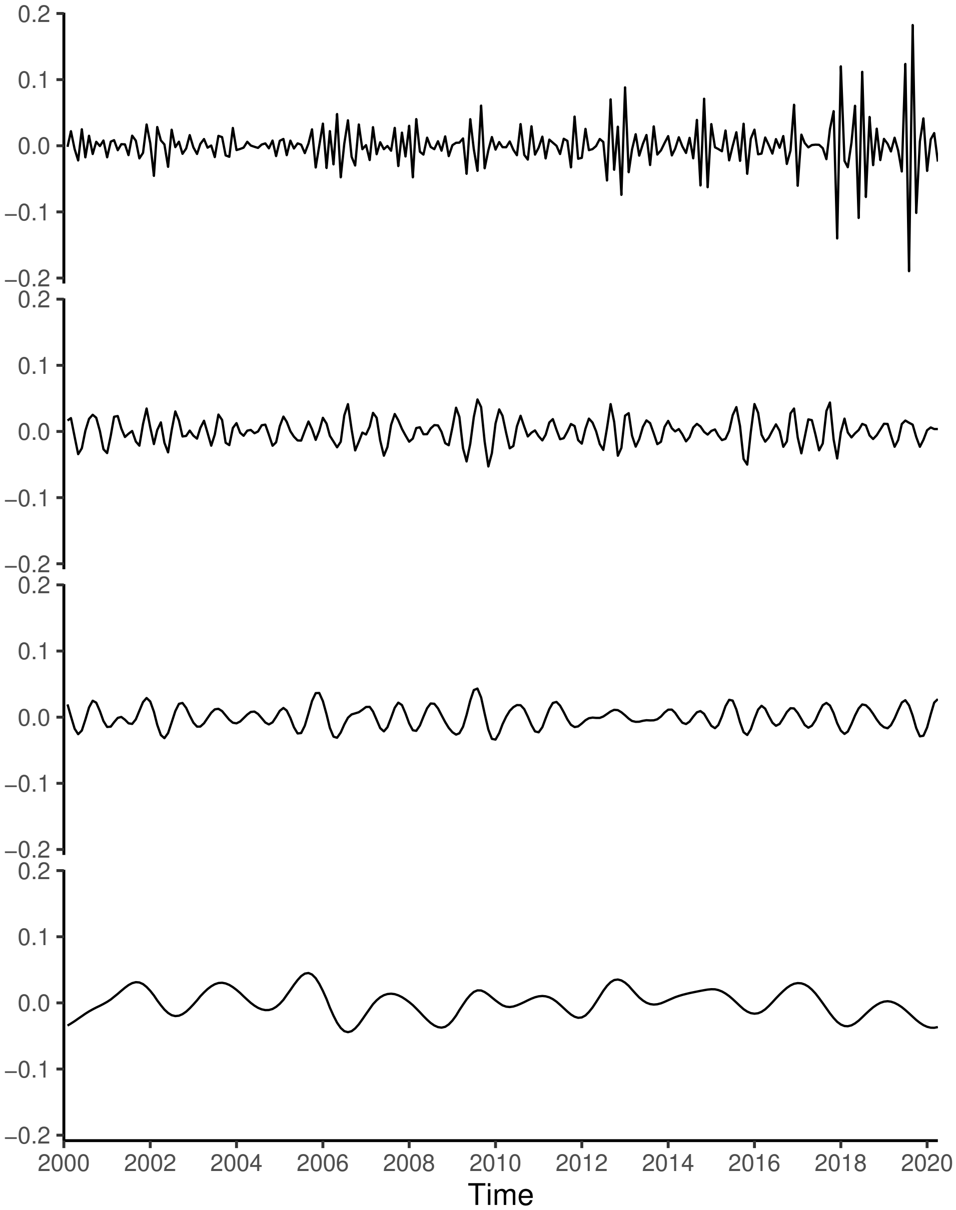

Figure 3: Wavelets of GRE: from top to bottom we have D1, D2, D3 (the three details) and S3 (the smooth), respectively.

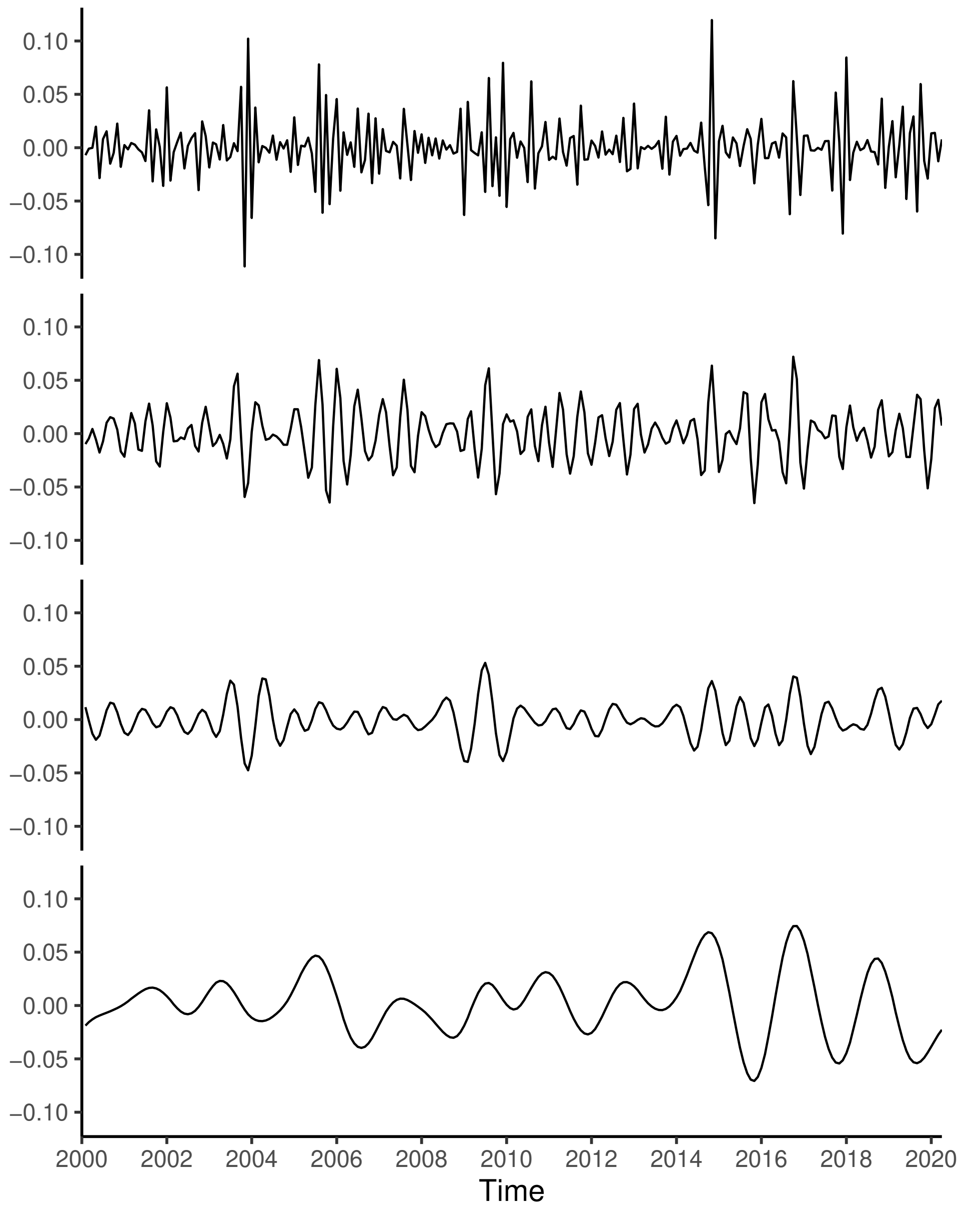

Figure 4: Wavelets of ITA: from top to bottom we have D1, D2, D3 (the three details) and S3 (the smooth), respectively.

In order to proceed with the estimation of the scale-by-scale copula functions, the filtered rates of price change, the details as well as the smooths have been converted to copula data using probability integral transforms and a scaling factor equal to T/T+1 (Emmanouilides and Fousekis, 2015a; Reboredo, 2012). For the estimation of the quantile dependence, we utilize the copula functions in (14) and (15). The estimated copulas are then employed in order to estimate dependence measures. Among the infinite number of such coefficients, the relevant literature has paid most of its attention on the tail dependence coefficients. The latter measure co-movement at the very extremes of a joint distribution. Accordingly, the lower tail dependence coefficient is the limit of a lower dependence coefficient as q goes to zero, whereas the upper tail dependence coefficient is the limit of an upper tail dependence coefficient as q goes to one.

In the case of the bivariate parametric copula families, even though explicit mathematical expressions for the tail dependence coefficients are available, their measurement, however, present various estimation problems. For a semi-parametric approach though, since explicit formulae exist, what is needed is to estimate tail coefficients are the estimates of the copula parameters. In the present manuscript, tail dependence estimation is based on non-parametric copulas. More specifically, if we set q close enough to zero (one), the sample estimate of λ_L^q (λ_U^q) assumes zero values as well. In order to overcome this problem, the employment of a 'cut-off' quantile measured in the neighbour of $1/\sqrt{T}$, with T being the sample size, can provide a reasonable solution to the aforementioned problem (Dobrić and Schmid, 2005). Estimates at the $1/\sqrt{T}$ quantile and at the $1-1/\sqrt{T}$ quantile can be considered as approximations for the lower and the upper tail dependence coefficients, respectively.

In the present study and following Fousekis and Grigoriadis (2016b), the quantile pairs 0.05/0.95 and 0.10/0.90 have been employed in order to evaluate dependence under extreme negative and extreme positive prices shocks, respectively, whereas the quantile pair 0.40/0.60 has been used to evaluate dependence under strong and weak negative and positive price shocks, respectively. The statistical test of symmetry by Patton (2013) has been employed in order to test for the presence of asymmetric price linkages.

Figures 5, 6, and 7, present the contour plots from the estimated copula probability density functions, by time scale, for the pairs of ESP/GRE, ITA/ESP and ITA/GRE, respectively.[4] In all three pairs, for the high frequencies, the probability mass is scattered around the joint support indicating weak intensity of dependence.

[4]For the computation and the derivation of the contour plots, the package "nonpar" in the R software has been used.

On the other hand, at the low frequencies, the probability mass generally tends to be concentrated closer to the positive diagonal suggesting stronger positive quadrant dependence.

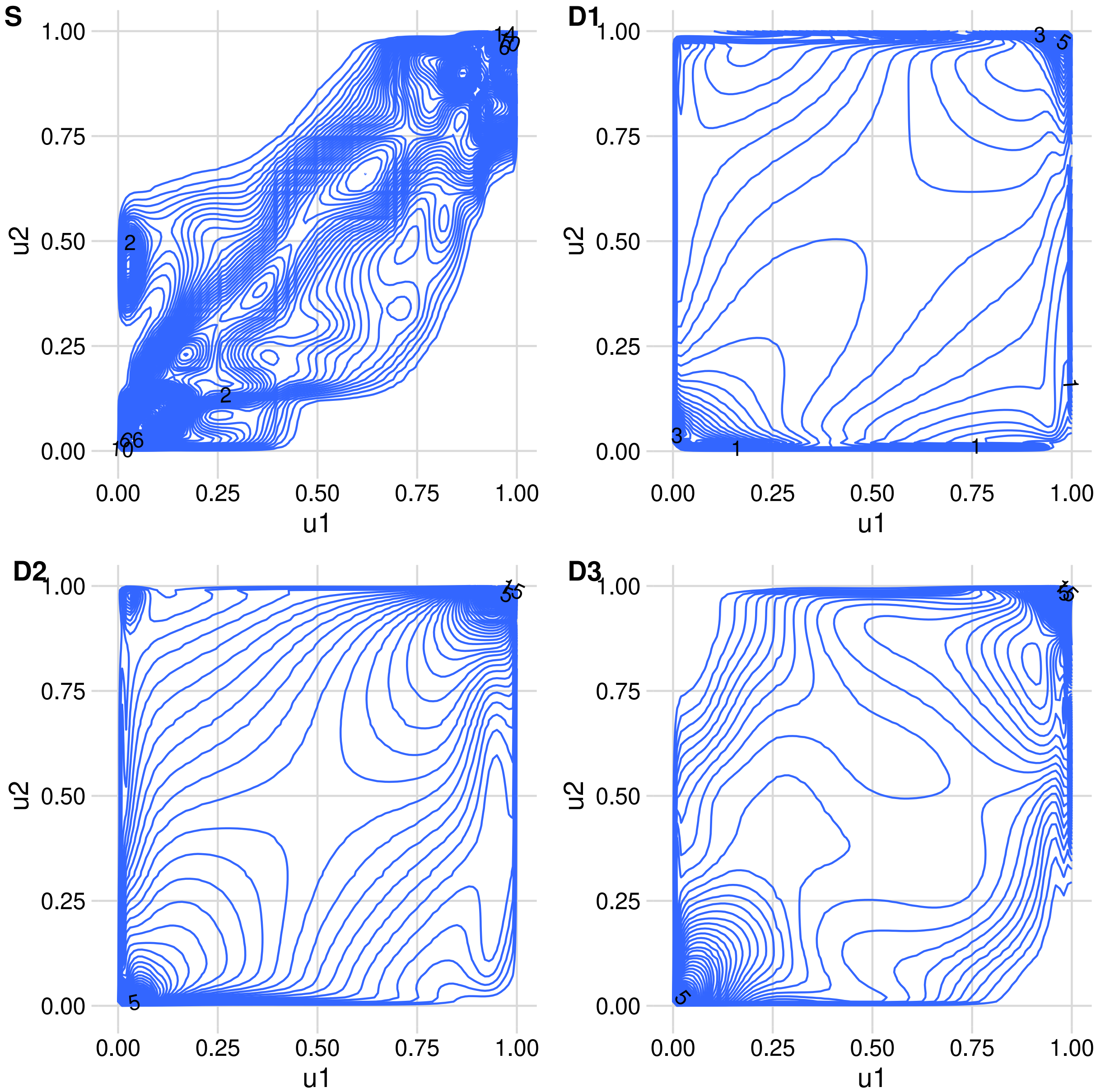

Figure 5: ESP/GRE non parametric copula

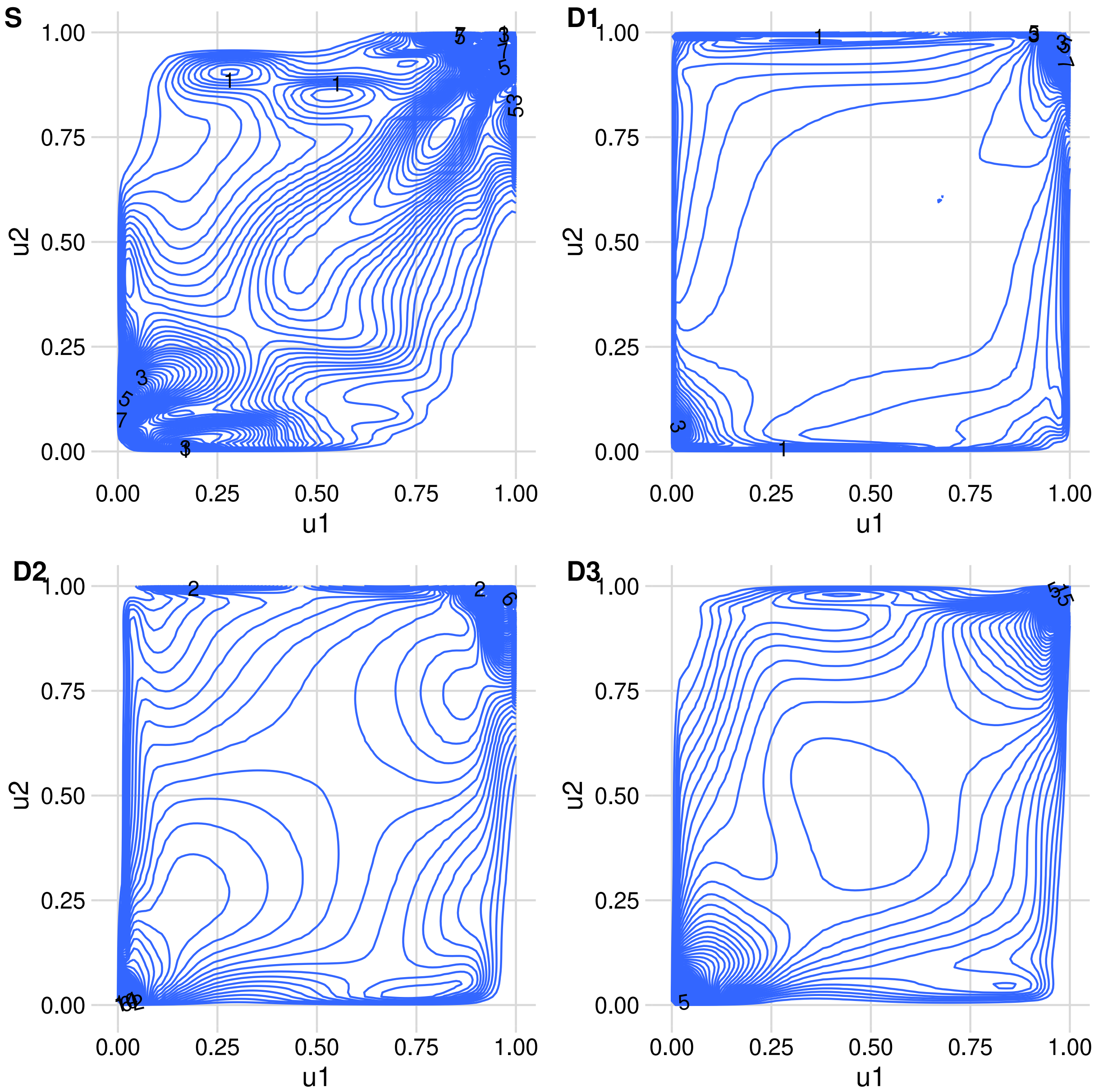

Figure 6: ITA/ESP non parametric copula

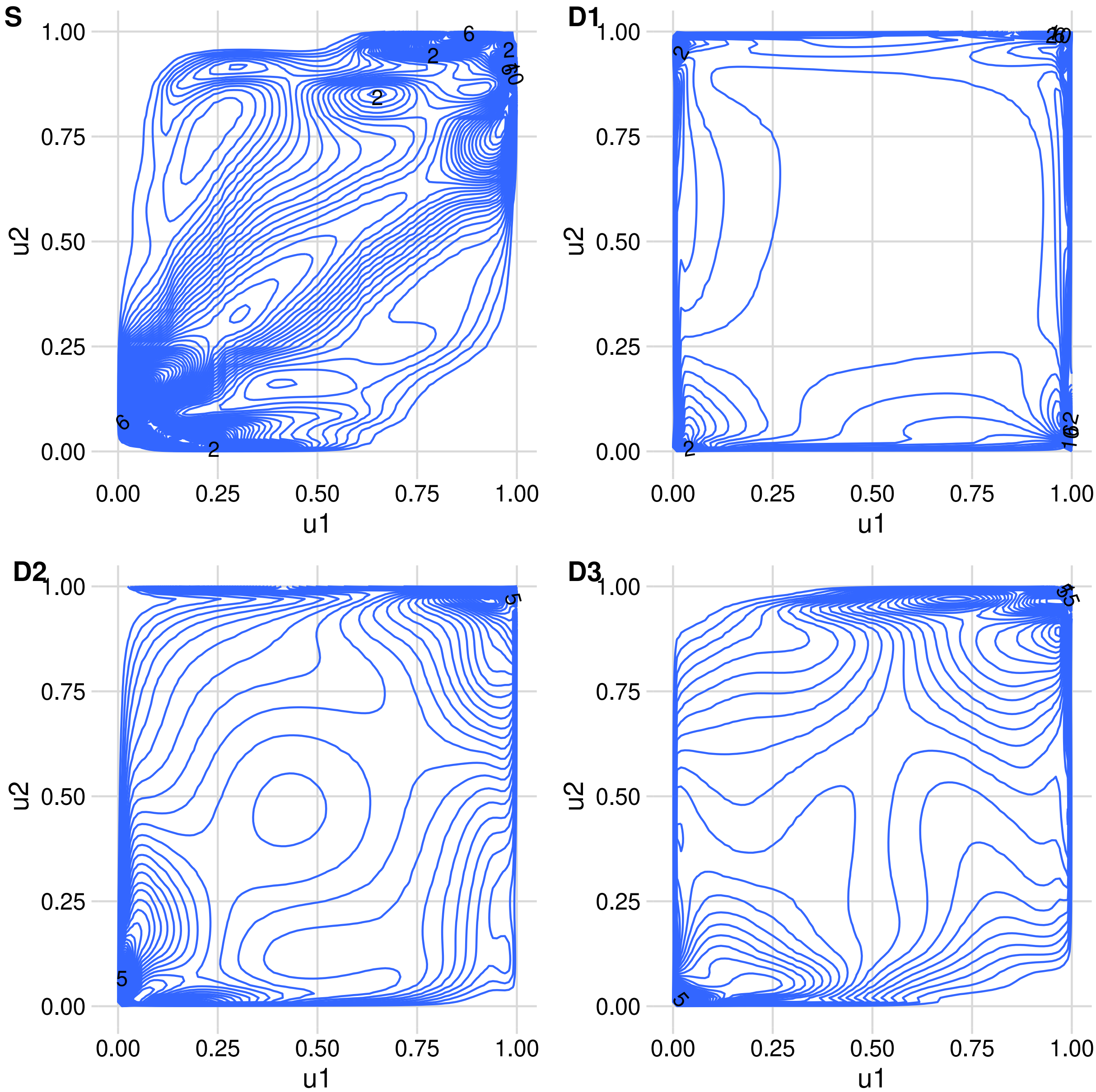

Figure 7: ITA/GRE non parametric copula

4.2 Results

Before proceeding with the empirical findings, we need to identify the causal markets. Causal markets are the markets from which the price shocks are originated. Emmanoulides et al. (2014) tested for the causal market(s) among Italy, Spain and Greece, for the case of the extra virgin olive oil. Results indicated that Italy is the causal market leading price changes in Spain and in Greece. Spain, however, leads price changes in Greece. The present study adopts and uses the findings obtained by Emmanoulides et al. (2014).

Tables 3, 4 and 5 present the estimates of quantile dependence coefficients along with their respective standard errors by time scale. The time scales examined in the present study are 2-4 months, 4-8 months, 8-16 months and larger than 16 months.

For the pair Spain-Greece (Table 3) and for the time scales from 2-4 months and higher, the lower (0.05) dependence coefficients and the upper (0.95) tail dependence coefficients tend to increase, suggesting that price linkages at both the upper and the lower part of the joint support become stronger with the time horizon. Hence, price crashes and/or price booms in Spain are more likely to be transferred to Greece in the longer run than in the short run. For time scales from 2 to 4 months, the lower tail dependence coefficient assumes a value zero, indicating that in the very short-run price crashes are not transmitted from Spain to Greece. For the time period beyond the sixteen months ($>$ 16 months), the value of the lower tail dependence coefficient quite big, assuming a value of 0.678. The aforementioned results indicate that in the time period beyond 16 months, large negative price shocks are transmitted from Spain to Greece with a much higher probability than large negative price shocks are transmitted in the short-run. On the other hand, for the time period 2-4 months, the upper tail dependence coefficient assumes a value (0.119) that is almost one quarter of the value of the upper tail dependence coefficient for the time period $>$ 16 months (0.461). Hence, extreme positive price shocks are transmitted from Spain to Greece with a much higher probability in the longer run than they do in the very short run.

The aforementioned results indicate it is not only the strength of price linkages that changes with the time scale but it is the structure of those linkages as well. The comparison of two upper (or two lower) quantile dependence coefficients provides information on the intensity by which price shocks of the same sign but of different magnitude are transmitted from one region to the other. To be specific, let us consider the values of the 0.90 and of the 0.60 quantile dependence coefficients for the highest scale ($>$ 16 months). These are 0.567 and 0.611 respectively, suggesting that the probability mass when the price shock in one region lies in the quantile interval [0.9, 1], which is $0.106 = 0.567 - 0.461$, is bigger than the interval that lies in the quantile interval [0.6, 0.9], which is 0.044 = 0.611–0.567. Given, however, that the latter interval is three times as wide as the former, the result implies that strong positive price shocks are likely to be transmitted with higher intensity compared to weaker positive price shocks. The same holds for almost all of the rest of the time scales for all positive price shocks. For purposes of clarification, we need to point out the relative "widths" of the quantile intervals are in terms of % of observations included and not in absolute sizes of the price shocks.

At this point we can investigate the same for the negative price shocks. Let us consider the values of the 0.10 and of the 0.40 quantile dependence coefficients for the for the highest scale ($>$ 16 months). These are 0.586 and 0.678 respectively, suggesting that the probability mass when the price shock in one region lies in the quantile interval [0.05, 0.10] is $0.09 = 0.678 - 0.586$, and the interval that lies in the quantile interval [0.1, 0.4] is $0.115 = 0.701 - 0.586$. Given, however, that the latter interval is six times as wide as the former, the result implies that strong negative price shocks are likely to be transmitted with higher intensity compared to weaker negative price shocks. The same holds for almost all of the rest of the time scales for all negative price shocks.

For the pair Italy-Spain (Table 4), for the time scale 2-4 months, the probability that price crashes and/or price booms will transfer from Italy to Spain is zero. For the time scale $>$ 16 months, price crashes do not transfer from Italy to Spain (probability is zero). Hence, in the very short run and in the longer run, price price crashes do not do not transfer from Italy to Spain.

Most of the activity appears to take place for the time scale 8-16 months. Strong and weaker price shocks (increases and decreases) appear to transfer with the highest intensity as compared to the rest of the time scales.

Furthermore, let us consider the values of the 0.90 and of the 0.60 quantile dependence coefficients for the aforementioned scale (8-16 months). These are 0.596 and 0.492 respectively, suggesting that the probability mass when the price shock in one region lies in the quantile interval [0.9, 1] which is $0.215 = 0.811 - 0.596$ is bigger than the interval that lies in the quantile interval [0.6, 0.9] (0.104 = 0.596–0.492). Given, however, that the latter interval is three times as wide as the former, the result implies that strong positive price shocks are likely to be transmitted with higher intensity compared to weaker positive price shocks. The same does not hold for the time periods 2-4 months and $>$ 16 months.

For the pair Italy-Greece (Table 5), for the time scale 2-4 months, the probability that price crashes will transfer from Italy to Greece is 0.226 and it is almost the same with the probability that price booms transfer from Italy to Greece in the very short run (0.227). For the time scale $>$ 16 months, price crashes and price booms do not transfer from Italy to Greece: the probability that a crash and/or a boom in prices in the Italian extra virgin olive oil will transfer to Greece is zero. Accordingly, for the time scale $>$ 16 months, price booms and price crashes do not transfer from Italy to Greece.

The comparison of two upper (or two lower) quantile dependence coefficients provides information on the intensity by which price shocks of the same sign but of different magnitude are transmitted from one region to the other. To be specific, let us consider the values of the 0.90 and of the 0.60 quantile dependence coefficients for the lowest time scale (2-4 months). These are 0.165 and 0.093 respectively, suggesting that the probability mass that lies in the quantile interval [0.6, 0.9] is $0.072 = 0.165 - 0.093$, whereas the probability mass when the price shock lies in the quantile interval [0.9, 1] is $0.062 = 0.227 - 0.165$. Given, however, that the latter interval is three times as wide as the former, the result implies that strong positive price shocks are likely to be transmitted with almost the same intensity compared to weaker positive price shocks. This implies that strong positive price shocks are likely to be transmitted with higher intensity compared to weaker positive price shocks.

Table 3: Dependence Coefficient ESP/GRE

Period	Quantile	Dep Coeff	Quantile	Dep Coeff	p-value for symmetry
2-4	0.05	0.000(0.001)	0.95	0.119(0.002)	0.012
	0.10	0.056(0.002)	0.90	0.184(0.003)	0.034
	0.40	0.307(0.002)	0.60	0.352(0.002)	0.872
4-8	0.05	0.422(0.004)	0.95	0.348(0.004)	0.764
	0.10	0.411(0.003)	0.90	0.362(0.004)	0.485
	0.40	0.458(0.002)	0.60	0.494(0.002)	0.795
8-16	0.05	0.274(0.003)	0.95	0.358(0.005)	0.658
	0.10	0.309(0.004)	0.90	0.433(0.004)	0.412
	0.40	0.432(0.003)	0.60	0.368(0.003)	0.541
> 16	0.05	0.678(0.005)	0.95	0.461(0.005)	0.345
	0.10	0.586(0.005)	0.90	0.567(0.005)	0.981
	0.40	0.701(0.003)	0.60	0.611(0.003)	0.853

Table 4: Dependence Coefficient ITA/ESP

Period	Quantile	Dep Coeff	Quantile	Dep Coeff	p-value for symmetry
2-4	0.05	0.000(0.001)	0.95	0.000(0.001)	0.742
	0.10	0.117(0.002)	0.90	0.203(0.003)	0.718
	0.40	0.178(0.002)	0.60	0.267(0.002)	0.435
4-8	0.05	0.455(0.004)	0.95	0.208(0.004)	0.389
	0.10	0.496(0.004)	0.90	0.288(0.003)	0.365
	0.40	0.354(0.003)	0.60	0.429(0.003)	0.672
8-16	0.05	0.656(0.004)	0.95	0.811(0.004)	0.541
	0.10	0.633(0.003)	0.90	0.596(0.004)	0.801
	0.40	0.495(0.003)	0.60	0.492(0.003)	0.952
> 16	0.05	0.000(0.001)	0.95	0.169(0.005)	0.023
	0.10	0.000(0.003)	0.90	0.378(0.004)	0.011
	0.40	0.525(0.002)	0.60	0.668(0.002)	0.769

Table 5: Dependence Coefficient ITA/GRE

Period	Quantile	Dep Coeff	Quantile	Dep Coeff	p-value for symmetry
2-4	0.05	0.226(0.004)	0.95	0.227(0.004)	0.951
	0.10	0.192(0.004)	0.90	0.165(0.003)	0.892
	0.40	0.210(0.003)	0.60	0.093(0.002)	0.453
4-8	0.05	0.161(0.005)	0.95	0.119(0.004)	0.789
	0.10	0.186(0.004)	0.90	0.143(0.003)	0.872
	0.40	0.361(0.002)	0.60	0.404(0.002)	0.675
8-16	0.05	0.202(0.004)	0.95	0.374(0.006)	0.569
	0.10	0.248(0.004)	0.90	0.228(0.005)	0.894
	0.40	0.336(0.003)	0.60	0.334(0.003)	0.987
> 16	0.05	0.000(0.001)	0.95	0.000(0.001)	0.894
	0.10	0.000(0.003)	0.90	0.090(0.003)	0.034
	0.40	0.655(0.002)	0.60	0.533(0.003)	0.765

4.3 Discussion

Prices in Spain and Greece (Table 3) boom together but they do not crash together in the very short run (2-4 months). In the short run, price co-movement between Spain and Greece reflects the fact that these two countries serve as necessary inputs to the blending/bottling industry in Italy, This is the case especially for Greece: 82% of the Greek olive oil production is extra virgin and 88% of Greek olive oil exports have Italy as their destination (Panagiotou, 2015).

On the other hand, in the longer run (t $>$ 16 months), the probability that extreme negative price shocks in Spain will transfer to Greece is higher when compared to the probability that extreme positive price shocks will. Hence, in the low time scale (2-4) months as well as in the high time scale months, asymmetry appears to be present since positive and negative shocks are transmitted with different intensities.

Price crashes and price booms in Italy do not transfer to Spain (Table 4) in the very short run (2-4 months). As a consequence, processors, consumers and primary producers in Spain are not likely to be affected by price crashes/boomd in Italy. The findings are quite different for the pair Italy - Greece (Table 4). Prices in Italy and Greece crash and boom together in the very short run (2-4 months), indicating that extreme positive and extreme negative price shocks in Italy will transfer to Greece with almost the same probability. Accordingly, processors, consumers and primary producers in Greece will be affected by price crashes and/or booms in Italy.

For the time scale beyond 16 months, only price booms in Italy will transfer to Spain. In the middle run, there is transmission of negative price shocks from Italy to Spain and Greece. The degree of transmission of negative price shocks from Italy to Spain and from Italy to Greece depends on two parameters. The first one is whether the producers in the exporting countries of Spain and Greece have access to different markets for their product. The second one is whether processors/blenders in Italy will keep on importing significant volumes of extra virgin olive oil from Spain and Greece because of its taste. Regarding the former, Spain has a significant share of approximately 20% in the world exports of olive oil and, therefore, access to different marketing channels. When it comes to the latter, Italian olive oil processing firms often use product differentiation as a tool for market segmentation and therefore they do not want to alter blends, even when domestic supply of olive oil becomes cheaper (Emmanoulides et al., 2014). When the aforementioned two conditions are in place, prices of extra virgin olive oil in Spain and in Greece will not fall along with a crash in the price of the Italian extra virgin olive oil. The empirical results of the present work suggest that these two conditions most likely hold.

For the time scale > 16 months ($t > 16$ months), the probability that extreme positive price shocks in Italy will transfer to Spain and Greece is larger when compared to the probability that extreme negative price shocks will. Hence, asymmetry seems to be present, for $t > 16$ months, for the pairs Italy-Spain and Italy-Greece. Positive price shocks in Italy will increase the demand for imports of extra virgin olive oil from Spain and Greece. When positive price shocks in Italy are transmitted to Greece and Spain, primary producers of extra virgin olive oil in Greece and Spain are likely to benefit from higher prices in the market of Italy. On the other hand, extra virgin olive oil processors in those two countries will probably experience an increase when purchasing their primary product. Lastly, consumers in Spain and Greece are likely to face higher prices for the purchase of extra virgin olive oil when a positive price shock takes place in Italy.

In 2006, the EU implemented the Single Market Review (SMR). With the initiation of the SMR, the EU started formally to pay attention on the price differences among member states in order to understand and explain the price adjustment mechanisms among the member states. According to the empirical findings of this work, for the pairs ITA-ESP and ITA-GRE, prices boom together but they do not crash together, especially in the short-run. These differences in the trends of dependence patterns between these three Mediterranean countries, might provide policy makers some useful insights when it comes to the product of extra virgin olive oil.

Finally, for the pair between Italy and Greece, the findings that in the short run price crashes and/or booms transfer from Italy to Greece whereas price crashes and/or booms do not transfer for t $>$ 16 months, might be significant information for the producers as well as for the blenders of extra virgin olive oil in Greece. The reason is that 82% of the Greek olive oil production is extra virgin and 88% of Greek olive oil exports have Italy as their destination (Panagiotou, 2015).

5 Conclusions

Well functioning integrated spatial markets are characterized by strong price linkages. The European Union, as a prime example, has been engaged in a process of market integration for a very long period of time. The objective of the present study has been to investigate price dependence by time scale, among the three major EU extra virgin olive oil markets. This has been pursued with the utilization of wavelets and copulas along with monthly observations of the extra virgin olive oil prices in Italy, Spain and Greece.

According to the empirical results, over the period from 2000 to 2020, there has been a variety of degrees and intensities of price linkages among the three geographically separated markets within the European Union. These can be summarized as:

- Price linkages in the short-run are significantly different from those in the longer-run. More specifically, price dependence is smaller at the very high frequencies (2-4 months) and bigger at the low frequency ones ($t > 16$ months).

This suggests that price dependence gets stronger in the longer-run. Hence, the time scale affects the pattern of dependence. The latter points to asymmetric price co-movement.

- For t $>$ 16 months, price shocks of the same sign but of different magnitude are transmitted from Italy to Spain with a higher probability than they are transmitted from Italy to Greece. Accordingly, the time scale affects the intensity of dependence.

- Lastly, when it comes to integration of the three markets, the asymmetric co-movement in most of the cases is not consistent with well-integrated markets.

There has been one earlier study by Emmanoulides et al. (2014) that investigated the integration of olive oil markets in the Mediterranean. The aforementioned work used copulas along with monthly data at the aggregates (net over all scales). For the case of the extra virgin olive oil, the results revealed asymmetric tail dependence coefficients for the pairs ITA-ESP and ITA-GRE. More specifically, the authors found that prices boom together in both pairs but they do not crash together (price crashes in Italy do not transfer to Spain or Greece). For the pair ESP-GRE the results suggested symmetric tail dependence: prices boom and crash together with the same probability. The authors concluded that there is evidence in favor of asymmetric price co-movements and suggested that the three major EU olive oil markets cannot be thought of as one great pool.

The empirical findings of the present work seem to verify the findings by Emmanoulides et al. (2014) regarding the intensity and strength of price linkages among the three pairs. Furthermore, this study, like the work by Emmanoulides et al. (2014), concluded that the degree of integration is very low in the short-run but, generally, much higher in the intermediate run among the three Mediterranean countries. Also, for most time scales the markets are likely to crash than to boom together (asymmetry in co-movement).

One potential avenue for future research may involve the use of continuous wavelets in order to examine price dependence between the three Mediterranean countries for the same commodity.

Appendix

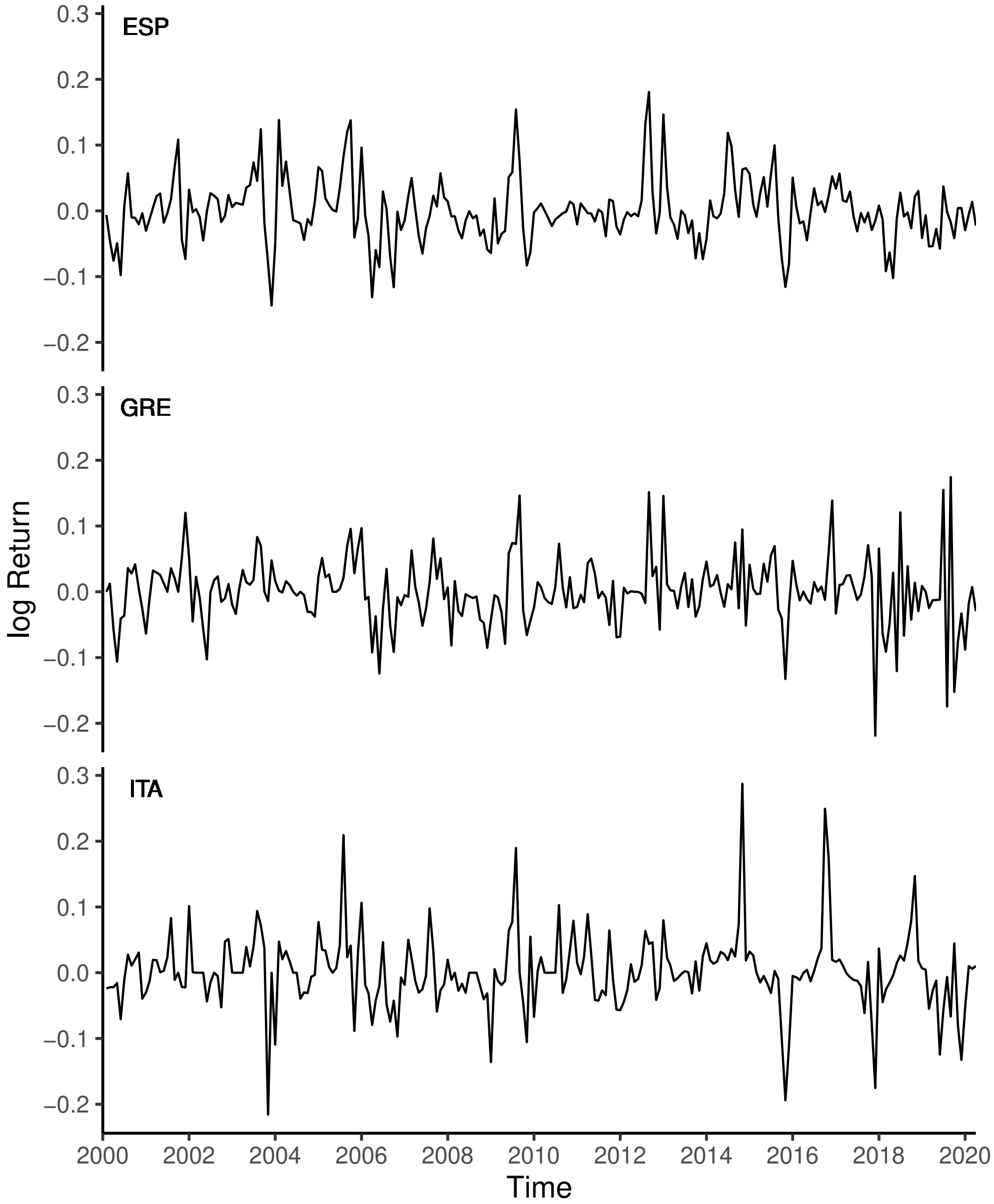

Figure 8: Time series of (log) returns of extra virgin olive oil prices.

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