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Price dependence in the principal EU olive oil markets

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Abstract

The objective of this paper is to assess the degree and the structure of price dependence in the principal EU olive oil markets (Spain, Italy and Greece). To this end, it utilizes monthly olive oil price data and the statistical tool of copulas. The empirical results suggest that prices are likely to boom together but not to crash together; this is especially true for the prices of the two most important players, Italy (importer) and Spain (exporter). The finding of asymmetric price co-movements implies that the three principal spatial olive oil markets in the EU cannot be thought of as one great pool.

Additional key words: efficiency; integration; co-movement; copulas.

Introduction

The European Union (EU) has been engaged in a process of market integration for a long period of time. A key element of that process was the adoption of the Single Market Programme which resulted in the removal of all barriers (tariff and non tariff ones) between national markets by January 1993. The idea behind the Single Market Programme was that the establishment of a large European market would foster competition and innovation, would increase the speed of adjustment and the resilience to economic shocks, and would benefit consumers through wider choices and lower prices. Soon, however, it became evident that the elimination of trade barriers was not enough and that a new impetus was necessary to fully exploit the potential of the market integration process. In response to the new challenges, the European Commission (EC) launched in 2006 the Single Market Review. The new strategy has placed its emphasis on understanding the price adjustment mechanisms to changing economic conditions making, thus, the single market policy more impact-driven and result-oriented (EC, 2012a). The cornerstone of the Single Market Review is market monitoring including benchmarking of price differences among the EU member states. A pilot study, conducted in the context of the Single Market Review, has indicated that the Food and Beverage industry was among the EU industries having potentially serious problems with regard to market integration (EC, 2008). The results of that pilot study appear to be in agreement with earlier survey evidence from supermarkets around the EU pointing to substantial and persistent price divergence for homogeneous products even in neighboring or in comparable countries (*e.g.* EC, 2004; Borchert & Reineke, 2007).

The analysis of spatial price interrelationships enable researchers to assess whether geographically separated markets are segmented (regionalized) or globalized (integrated). Economic Theory predicts that in the absence of trade barriers, spatial arbitrage activities will ensure that the price difference of a homogeneous commodity in two geographically separated markets will be, at most, equal to transportation/transaction costs [the weak version of the Law of One Price (LOP)]. Under spatial market segmentation, profitability opportunities are not fully exploited resulting into efficiency losses (*e.g.* Asche *et al.*, 1999; Serra *et al.*, 2006; Reboredo, 2011).

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This work has two Supplementary Tables that do not appear in the printed article but that accompany the paper online.

Abbreviations used: AIC (Akaike Information Criterion); BIC (Bayesian Information Criterion); CvM (Cramér-von Mises); EC (European Commission); ES (Spain); EU (European Union); GR (Greece); IT (Italy); KS (Kolmogorov-Smirnov); LLR (Local Linear Regression); LOP (Law of One Price); TAR (Threshold Autoregressive).

Although market globalization, in general, and food market integration in particular, has been an issue of great importance for both economists and policy makers, the number of recent formal studies on the price interrelationships and/or on the validity of the LOP for spatial EU agri-food markets has been rather small. Serra *et al*. (2006) investigated price adjustment (which is a necessary but not a sufficient condition for the LOP to hold) among four major EU pork markets using both the parametric Threshold Autoregressive Model (TAR) and the non parametric Local Linear Regression (LLR) models. They found evidence of asymmetries in price transmission. Fousekis (2007) assessed the validity of the LOP for pork and poultry in fourteen EU markets using multivariate linear cointegration tests. He obtained some evidence of the LOP in the pork markets but very limited evidence of it in the poultry markets. Emmanouilides & Fousekis (2012) also examined the validity of the LOP in four major pork markets using bivariate non linear stationarity tests. According to their results the LOP holds for the markets considered.

Against this background, the objective of the present work is to assess the degree and the structure of price dependence in the principal EU olive oil markets. To the best of our knowledge, there are no publicly available econometric studies that address price dependence in these particular markets. To provide a formal analysis, we utilized price data from Spain, Italy, and Greece, and the statistical tool of copulas. In the recent years the EU production of olive oil has been approximately 3.5 million tonnes (75% of the world production). The three principal producers (Spain with 60%, Italy with 21%, and Greece with 14%) account for about 95% of the EU production. The EU is also the world's biggest consumer of olive oil (with a share of 66%); Spain, Italy, and Greece account for about 80% of the EU consumption.

In statistics, copula is a joining function; it brings together the marginal distributions of individual random processes to obtain their joint distribution. The use of copulas for modeling dependence among random processes gained momentum in the late 1990s especially in engineering, risk management, and finance but only very recently has found its way into applied and agricultural economics. Standard tools for the analysis of multivariate structures assume that the marginal distributions belong to the same family (typically the normal distribution) and often that the dependence structure follows a linear relationship. A distinct advantage of copulas is that they allow the joint behavior of random processes (which is of primary interest) to be modeled independently of the marginal distributions – an approach that offers considerable flexibility in empirical research (*e.g*. Nelsen, 2006; Patton, 2012; Requenta *et al*., 2013). With regard to spatial price interrelationships, the notion behind employing copulas to characterize co-movement (dependence) is that in well-integrated markets, prices move together; specifically, they boom and they crash together. Copulas are especially suitable for modeling the joint behavior of random processes during extreme events, making it possible to assess whether prices are linked with the same intensity at both extreme market upturns and downturns (Reboredo, 2011).

To date, there have been few studies employing copulas to analyze market integration. Goodwin *et al*. (2011) examined spatial price adjustments in four timber markets of North America and found evidence of asymmetries at the tails of the joint distributions. Reboredo (2011) assessed price dependence in four regional crude oil markets. He reported symmetric tail co-movements, something which suggests that the markets under consideration constitute one great pool. Serra (2012) investigated dependence between biodiesel, diesel, and crude oil prices in Spain. According to her results, there has been symmetric price co-movement for the crude oil-diesel pair but only lower-tail dependence for the crude oil-biodiesel pair.

Material and methods

Copulas and dependence measurement

Let $X=(X_1,X_2)$ be a random vector with distribution function $H(x_1,x_2)$; let also $H_1(x_1)$ and $H_2(x_2)$ be the marginal distribution functions of X_1 and X_2 respectively[1]. Then, according to Sklar's (1959) theorem, there exists a copula function $C:[0,1]^2 \rightarrow [0,1]$ such that for all $(x_1,x_2)\in R^2$ it is the case

$$H(x_1,x_2) = C\{H_1(x_1), H_2(x_2)\} \quad [1]$$

[1] For the sake of simplicity we consider the bivariate case. The results, however, can be readily extended to a p-variate case with $p>2$. Details related to the construction and the properties of copulas can be found in Joe (1997), Nelsen (2006), Genest & Favre (2007), and Patton (2012).

For continuous marginal distributions, the copula function is unique and has the representation

$$C(u_1,u_2) = H(H_1^{-1}(u_1), H_2^{-1}(u_2)) \qquad [2],$$

where H_i^{-1} $(i=1,2)$ are the inverse distribution functions (marginal quantile functions) and are quantiles (probabilities) of the uniform distribution function, $U[0,1]$. The joint density function associated with C is

$$c(u_1,u_2) = \frac{\partial^2 C}{\partial u_1 \partial u_2} = \frac{h(H_1^{-1}(u_1), H_2^{-1}(u_2))}{h_1(H_1^{-1}(u_1))h_2(H_2^{-1}(u_2))} = \\ = \frac{h(x_1,x_2)}{h_1(x_1)h_2(x_2)} \qquad [3],$$

where h is the joint density function of H, h_1 and h_2 are, respectively, the marginal density functions of H_1 and H_2. From [3] follows

$$h(x_1,x_2) = c(H_1(x_1), H_2(x_2))h_1(x_1)h_2(x_2) \qquad [4].$$

A joint probability density function of two random variables contains information on the marginal behavior of X_1 and X_2 and on the dependence between them. In $c(F_1(x_1),F_2(x_2))$ each random variable is fed on its own distribution function. As a result, all information contained in the marginal distribution functions is swept away and what is left in c (and in C) is pure joint information about X_1 and X_2. From [4] it is clear that the copula fully characterizes the co-movement (dependence) of the random variables by capturing the information missing from the marginal distributions to complete the joint distribution (Meucci, 2011). The converse of Sklar's theorem holds and it states that given H_1 and H_2 and any copula function C, the function H in [1] defines a valid joint distribution function with margins H_1 and H_2.

Conducting inference on dependence (co-movement) using copulas offers a number of advantages. First, just as marginal distributions provide an exhaustive description of the behavior of two random variables when considered separately, copulas fully and uniquely characterize the dependence structure between X_1 and X_2. Second, copulas are able to model co-movement independently of the marginal distributions. This follows from the converse of Sklar's theorem. Third, copulas provide information on the degree as well as the structure of dependence; as known, standard measures of co-movement such as Pearson's correlation coefficient provide information regarding whether X_1 and X_2 are linearly related. Copulas, in contrast, allow for more general forms of functional dependence between the two variables, with linear co-movement being a special case. Fourth, because copulas are based on the ranks of X_1 and X_2, they are invariant to continuous and monotonically increasing transformations of them.

A standard rank-based measure of functional dependence is Kendall's , defined as

$$\tau_N = \frac{P_N - Q_N}{\binom{N}{2}} = \frac{4P_N}{N(N-1)} - 1 \qquad [5],$$

where N is the total number of observations, and P_N and Q_N are the number of concordant and discordant pairs, respectively; two pairs (x_{1j},x_{2j}), (x_{1k},x_{2k}), $j,k=1, 2,\ldots, N$, are said to be concordant (discordant) when $(x_{1j}-x_{1k})(x_{2j}-x_{2k})>0$ (<0). Kendall's τ provides information on co-movement across the entire joint distribution function (at the center, as well as at the tails of it).

The relevant notion for the study of co-movement between extreme values is that of tail dependence, relating to the amount of dependence in the upper-right and/or the lower left quadrant tails of a bivariate distribution. Tail (extreme) co-movement is measured by the upper,λ_U, and the lower, λ_L, dependence coefficients defined as

$$\lambda_U = \lim_{u\to 1^-} prob(X_1 > H_1^{-1}(u) / X_2 > H_2^{-1}(u)) = \\ = \lim_{u\to 1^-} prob(U_1 > u / U_2 > u) = \qquad [6] \\ = \lim_{u\to 1^-} \frac{1-2u+C(u,u)}{1-u} \in [0,1]$$

and

$$\lambda_L = \lim_{u\to 0^+} prob(X_1 < H_1^{-1}(u) / X_2 < H_2^{-1}(u)) = \\ = \lim_{u\to 0^+} prob(U_1 < u / U_2 < u) = \qquad [7]. \\ = \lim_{u\to 0^+} \frac{C(u,u)}{u} \in [0,1]$$

λ_U measures the probability that X_1 is greater than the 100u-*th* percentile of F_1, given that X_2 is also greater than the 100u-*th* percentile of F_2 as u approaches 1 from below; λ_L measures the probability that X_1 is less than the 100u-*th* percentile of F_1, given that X_2 is also less than the 100u-*th* percentile of F_2 as u approaches 0 from above. In other words, the two coefficients of tail dependence provide information about the likelihood for the two random variables to boom and to crash together, respectively. Note that since λ_U and λ_L in [6] and [7] are expressed via copula, certain properties of copulas (*e.g.* invariance to monotonically increasing transformations of the underlying random variables) apply to tail coefficients as well.

Commonly used families of bivariate copulas: parameters and implied dependence structures

Given that multivariate stochastic processes may have quite different properties, it is highly desirable for a researcher to have at her (his) disposal a variety of copulas to capture adequately the salient characteristics (*e.g.* asymmetries, heavy tails) of the processes to be modeled. According to Durante & Sempi (2010), a "good" family of copulas is: (a) interpretable, meaning that its members have a probabilistic interpretation suggesting "natural" situations where this family could be considered; (b) flexible, meaning that its members are capable of representing many possible types and degrees of co-movement; (c) easy-to-handle, meaning that the family members are expressed in a closed form or, at least, are easily simulated by means of some known algorithm. The investigations on the topic have led to a very large number of copula families with desirable properties. In the following, the paper presents and discusses only those typically employed in finance, risk management, and economics (*e.g.* Embrechts *et al.*, 2002; Goodwin *et al.*, 2011; Reboredo, 2011; Czado *et al.*, 2012; Patton, 2012; Serra & Gil, 2012).

The *Gaussian* and the *t-copula* are members of the *elliptical* family of copulas. The Gaussian involves a single dependence parameter, ρ (the linear correlation coefficient corresponding to the bivariate normal distribution). The *t*-copula involves two parameters, the correlation coefficient ρ and the degrees of freedom (denoted as v). When $v \geq 30$ the *t*-copula collapses to a Gaussian one. The Clayton, the Gumbel, the Frank, the Gumbel-Clayton, and the Joe-Clayton are members of the family of *Archimedean* copulas. The first three contain a single dependence parameter (denoted as θ) while the last two contain two dependence parameters (denoted as θ_1 and θ_2).

Table 1 presents the relevant dependence parameter(s) and their relationship to Kendall's as well as to the upper and lower dependence coefficients[2]. The Gaussian copula is symmetric and exhibits zero tail dependence. That is, irrespective of the degree of the overall dependence, extreme changes in one random variable are not associated with extreme changes in the other random variable. The *t*-copula exhibits symmetric non-zero tail dependence (joint booms and crashes have the same probability of occurrence). The Clayton copula exhibits only left co-movement (lower tail dependence); the Gumbel copula exhibits only right co-movement (upper tail dependence); the Frank copula exhibits zero tail dependence; the Gumbel-Clayton and the Joe-Clayton copulas allow for (potentially asymmetric) both right and left co-movement.

The semiparametric approach

In our empirical analysis we use the semiparametric approach (Chen & Fan, 2006). In the first stage of this approach, the original series are transformed into the so called copula data (meaning data with approximately uniform marginal distributions on [0,1]) using their respective empirical distribution functions. In the second stage, the estimation of parametric copula models is carried out by applying the maximum likelihood estimator on the copula data (method of maximum pseudo-likelihood). The Suppl. Table 1 [pdf online] presents technical details on the construction of the copula data and on the method of maximum pseudo-likelihood.

The semiparametric estimator of the copula parameter vector $\hat{\theta}$ is consistent and asymptotically normal. It is, however, inefficient when the original series are not i.i.d., something that it is often the case with time series data. This problem has been typically addressed in the relevant literature in two alternative methods: (a) Parametric GARCH models, one for each series, are fit to the original data and the empirical distribution functions are obtained from the resulting series of standardized innovations; (b) standard errors of the parameters of interest (*e.g.* those of average and tail dependence) are approximated using resampling methods (*e.g.* Choros *et al.*, 2010). Here, we employ the second methodology. As shown by Kim *et al.* (2007) an inappropriate choice of the parametric models in the first stage may have a detrimental effect on the estimation of the dependence parameters *per se*. Moreover, the first method renders inference on co-movement very difficult because any hypothesis about

[2] Joe (1997) and Nelsen (2006) offer functional forms for the family of the elliptical copulas and generator functions for the family of Archimedean copulas.

Table 1. Copula parameters, Kendall's τ, and tail dependence[1]

Copulas	Parameters	Kendall's τ	Tail dependence (lower, upper)
Gaussian	$\rho \in (-1, 1)$	$\frac{2}{\pi}\arcsin(\rho)$	(0,0)
t-Copula	$\rho \in (-1, 1)$, $v > 2$	$\frac{2}{\pi}\arcsin(\rho)$	$(2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{\frac{1-\rho}{1+\rho}}),$ $2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{\frac{1-\rho}{1+\rho}}))$
Clayton	$\theta > 0$	$\frac{\theta}{\theta+2}$	$(2^{-\frac{1}{\theta}}, 0)$
Gumbel	$\theta \geq 1$	$1-\frac{1}{\theta}$	$(0,\ 2-2^{\frac{1}{\theta}})$
Frank[2]	$\theta \in R \setminus \{0\}$	$1-\frac{4}{\theta}+4\frac{D(\theta)}{\theta}$ [2]	(0,0)
Gumbel-Clayton	$\theta_1 > 0,\ \theta_2 \geq 1$	$1-\frac{2}{\theta_2(\theta_1+2)}$	$(2^{-\frac{1}{\theta_1\theta_2}},\ 2-2^{\frac{1}{\theta_2}})$
Joe-Clayton	$\theta_1 \geq 1,\ \theta_2 > 0$	$1+\frac{4}{\theta_1\theta_2}\int_0^1(-(1-(1-t)^{\theta_1})^{\theta_2+1}$ x $\frac{(1-(1-t)^{\theta_1})^{-\theta_2}-1}{(1-t)^{\theta_2-1}})dt$	$(2^{-\frac{1}{\theta_2}},\ 2-2^{\frac{1}{\theta_1}})$

(1) Brechmann & Schepsmeier (2013). (2) $D(\theta)=\int_0^{\theta_1}\frac{c/\theta}{\exp(x)-1}dx$ is the Debye function.

the dependence structure becomes composite, as it actually concerns both the employed parametric GARCH models and the employed parametric copula model (Genest *et al.*, 2009).

The selection among the seven alternative copula families, presented above, is carried out in the following way. In a first step, the the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are applied to each family[3]. In the case where the two criteria are in agreement, the selection process is terminated with the appropriate (the best fitting) model being the one that gives the lower AIC (and BIC) value. In the case of disagreement, the goodness of fit of the two competing models is further assessed using the rank-based versions of the Kolmogorov-Smirnov(KS) and the Cramer-von Mises (CvM) tests (Suppl. Table 2 [pdf online]). All estimations and tests have been carried out using the CDVine package in R (Schepmeier & Brechmann, 2012).

The data and the empirical models

The data we use for the empirical analysis are monthly olive oil prices (expressed in Euros per 100 kg) from Spain, Italy, and Greece[4]. In particular, we con-

[3] The values of the AIC and the BIC criteria are computed from

$$AIC := -2\sum_{i=1}^{N}\ln[c_\theta(u_{1i},u_{2i})]+2k, \quad BIC := -2\sum_{i=1}^{N}\ln[c_\theta(u_{1i},u_{2i})]+\ln(N)k$$

where k is the number of the estimated dependence parameters.

[4] Obtained from the EC (2013). They correspond to the prices received by producers at the factory gate for olive oil in bulk.

sider the prices of two quality differentiated olive oil grades; extra virgin and lampante. On the basis of the relevant EC Regulation, 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 which have not undergone any treatment other than washing, decantation, centrifugation or filtration. Extra virgin oil has a maximum of 0.8 g oleic acid per 100 g of oil. Lampante oil refers to olive oils obtained from the pressing of rotten olives, gathered from the ground when fermentation has already set in; it has from 2 to 5 g of oleic acid per 100 g of oil[5]. Because of its acidity and its bad taste, lampante oil is not suitable for consumption. It has to be refined through a chemical process using phosphoric acid, caustic soda, clays, and very high temperatures, and also to be blended with some (between 5% and 20%) extra virgin olive oil to give it taste and color.

Fig. 1a presents the natural logarithms of prices of extra virgin olive oil and Fig. 1b those of lampante olive oil over the period 2002:1 to 2012:12. With respect to extra virgin olive oil, Italy (IT) has been the spatial market with the higher price. Prices of this commodity in Greece (GR) and in Spain (ES) have been quite similar to each other. The observed price differences reflect primarily differences in supply and demand conditions; prices tend to be higher in a deficit market (IT) relative to those in surplus markets (ES and GR). Overall, the three price series appear to be moving together with the exception of (approximately) the period October 2010 to December 2011[6]. With respect to lampante olive oil, Greece has been the spatial market with the lower price, while the prices of this commodity in Italy and Spain have been very close to each other. The three price series appear to be moving together throughout the period considered here.

Among the three principal EU olive oil markets there are certain differences both in terms of the olive quality produced as well as in terms of consumption models. In Spain, 35% of the total olive oil production is extra virgin, 32% is virgin, and 33% is lampante. The respective figures for Italy are 59%, 18%, and 24%. In Greece, more than 80% of total production consists of extra virgin olive oil. With regard to consumption models, Italy and Greece consume primarily extra virgin olive oil whereas in Spain this category represents less than 50% of the total olive oil consumption (EC, 2012b).

As far as the Intra-Community trade is concerned, 72% of Spain's exports and 88% of Greece's exports have Italy as their destination; 98% of Italy's imports from EU members come from Spain and Greece (EC, 2012c). The exports of Spain and Greece to Italy consist to a large extent of extra virgin and virgin olive oil, sold in bulk; these are subsequently bottled and/or blended by a small number of major Italian companies (the downstream level of the olive oil chain in Italy is highly concentrated) and are sold at the international markets. It is noteworthy that although Italy is a deficit

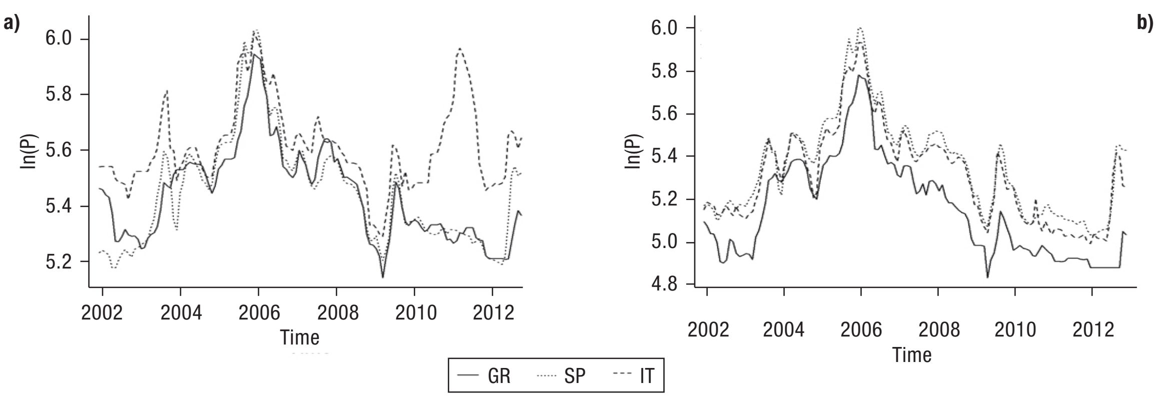

Figure 1. Natural logarithms of (a) virgin olive oil prices and (b) lampante olive oil prices. GR = Greece. SP = Spain. IT = Italy.

[5] There are other categories or subcategories of olive oil: the virgin olive oil with acidity from 0.8 to 2, the olive-pomace oil, and the refined olive oil. These have been left out of the analysis because of data problems (incomplete time series for the most recent years).

[6] The hike in price at the Italian market has been attributed to a rise in production costs (Advisory Group on Olives and Derived Products – Report of the 7th of June 2011 Meeting, Brussels).

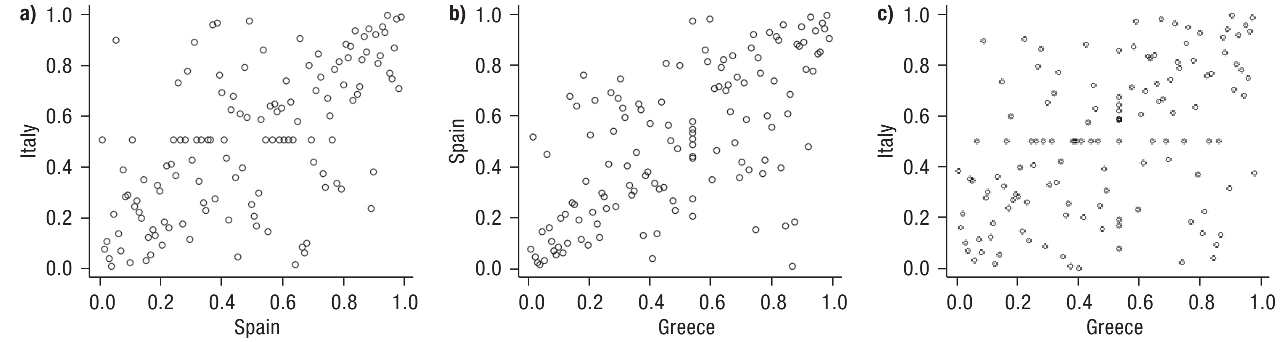

Figure 2. Scatterplots of normalized ranks. Extra virgin olive oil.

market within the EU, it is a major olive oil exporter in the world with a share of about 30%; Spain's share is 18%. There are trade flows between Spain and Greece but they are very limited when compared with those of the two countries with Italy.

Following earlier works on price dependence (*e.g.* Reboredo, 2011; Serra & Gil, 2012) we focused on the co-movements between the rates of price change at the three spatial markets. In particular, we denoted $\hat{p}_{it}$ and $\hat{p}_{jt}$ the rates of price change, at time t, in markets i and j, respectively (i,j = IT,GR,ES), and we analyzed the joint distribution of these two random variables with copulas. In this framework, an empirical finding (say) that a t-copula adequately represents the dependence structure of the bivariate random process will imply that positive and negative price shocks are likely to be transmitted from one spatial market to the other with the same intensity. However, an empirical finding that the Joe-Clayton copula adequately represents the same dependence structure will imply that positive and negative shocks are transmitted from one spatial market to the other with different intensities.

Figs. 2 (a-c) and 3 (a-c) present scatterplots of normalized ranks for ES-IT, ES-GR and IT-GR price change pairs, for extra virgin and for lampante olive oil, respectively. Starting with Fig. 2, the majority of rank pairs lies along the respective positive diagonals, suggesting positive association between the rates of price change in the three spatial markets. The dispersion, however, of rank pairs along the positive diagonal appears to be greater for IT-GR compared to IT-ES and to ES-GR. This is an indication that Italian and Greek markets are not interconnected as strongly as the other two country pairs. The information conveyed from the examination of the scatterplots for lampante olive oil is simlar; the interconnection between Italy and Spain appears to be stronger while that between Italy and Greece appears to be weaker.

Results

Focusing on the spatial markets for extra virgin olive oil first, both the AIC and the BIC criteria have selected the one-parameter Gumbel copula for ES-IT and IT-GR and the two-parameter t-copula for ES-GR. Table 2 presents parameter estimates from the selected copula models.

For the pair IT-ES, the Gumbel copula points to dependence in the upper-right-quadrant tail only; virgin

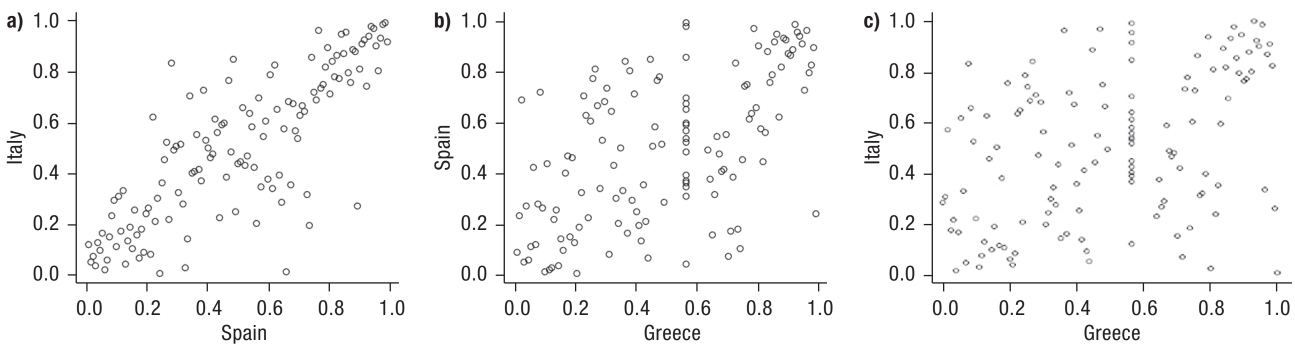

Figure 3. Scatterplots of normalized ranks. Lampante olive oil.

Table 2. Extra virgin olive oil. Copula parameter estimates(1)

Spatial market pairs	Selected copula	Parameters	Kendall's τ	λ_L	λ_U
ES-IT	Gumbel	θ = 1.775 (0.129)	0.436 (0.049)	0	0.522 (0.05)
ES-GR	*t*-Copula	θ = 0.690 (0.052) θ = 3.178 (1.298)	0.485 (0.047)	0.463 (0.083)	0.463 (0.083)
IT-GR	Gumbel	θ = 1.471 (0.103)	0.320 (0.052)	0	0.398 (0.057)

(1) Standard errors for Kendall's τ and for the tail dependence coefficients have been obtained using the jackknife method (Efron, 1979).

olive oil prices in those two markets are likely to boom together but not to crash together. The value of the upper tail dependence coefficient suggests that with a (statistically significant) probability of 0.522, a strongly positive rate of price change in one of the two markets will be matched with a similarly strong positive rate of price change in the other market. Kendall's τ has a value of 0.436, indicating that although the concordant pairs well exceed the discordant ones, the overall strength of the relationship between the rates of price change is not very high.

For the pair ES-GR, the *t*-copula points to fat tails and to symmetric tail dependence; the degrees of freedom is about 3.2 (well below 30), suggesting a very strong departure from normality, while Kendall's τ is very close to 0.5. The tail dependence coefficients are statistically significant at any reasonable level and suggest that with a probability of 0.458, prices in Greece and in Spain boom and crash together.

For the pair IT-GR, the Gumbel copula indicates co-movement in the upper-right-quadrant tail, only. The (statistically significant) probability of a mutual boom in prices is 0.398, while the Kendall's τ is 0.32, indicating that co-movement over the entire distribution function is lower compared to the other two market pairs.

With respect to the spatial markets of lampante olive oil, both the AIC and the BIC criteria selected the one-parameter Gumbel copula for ES-IT and ES-GR; they were, however, in disagreement for IT-GR. In particular, the AIC criterion selected the two-parameter *t*-copula and the more conservative BIC criterion selected the one-parameter Gumbel copula. To eliminate this ambiguity, the fit of the two competing copulas was further assessed using the rank-based versions of the KS and the CvM tests. The KS and the CvM tests (shown in Table 3) did not reject the *t*-copula. The KS test, however, rejected the Gumbel copula at the 10% level. Moreover, the *p*-values of both tests for the *t*-copula were twice as high as those for the Gumbel copula. It appears, therefore, that the *t*-copula has a better fit on the data compared to the Gumbel one.

Table 4 presents parameter estimates for the selected copula models. For IT-ES, the Gumbel copula points to dependence in the upper-right-quadrant tail only. The value of the upper dependence coefficient suggests that with a (statistically significant) probability of 0.695, a strongly positive rate of price change in one of the two markets will be matched with a comparably strong positive rate of price change in the other market. Kendall's τ has a value of 0.616, indicating that the overall strength of the relationship between the two spatial rates of price changes is quite high. For ES-GR, the upper tail dependence coefficient was 0.486 and the Kendall's τ was 0.402. For IT-GR, the symmetric coefficients of extreme co-movement have been 0.323 (and statistically significant at the 10% level) while Kendall's τ has been substantially lower compared to the other two pairs (0.285).

To assess the plausibility of the empirical results from the copula models and to elaborate about their likely implications, it is necessary to bring several pieces of information together. Specifically, it is important to: (a) identify the causal market(s) —as known, causal is the market from which price shocks

Table 3. Lampante olive oil. Rank-based CvM and KS tests for the pair IT-GR(1)

Copula test	*t*-Copula		Gumbel	
	Statistic	*p*-value	Statistic	*p*-value
CvM	0.107	0.232	0.130	0.124
KS	0.843	0.186	0.925	0.098

(1) Based on 500 samples using the bootstrap proposed by Genest *et al.* (2009).

Table 4. Lampante olive oil. Copula parameter estimates[(1)]

Spatial market pairs	Selected copula	Parameters	Kendall's τ	λ_L	λ_U
ES-IT	Gumbel	θ = 2.604 (0.191)	0.616 (0.031)	0	0.695 (0.028)
ES-GR	Gumbel	θ =1.673 (0.118)	0.402 (0.046)	0	0.486 (0.048)
IT-GR	*t*-Copula	θ = 0.438 (0.079) ν = 4.247 (2.036)	0.285 (0.061)	0.323 (0.196)	0.323 (0.196)

[(1)] The Kendall's τ and the tail dependence coefficients with their respective standard errors have been obtained using the jackknife method (Efron, 1979).

are originated—, (b) consider which are the surplus and the deficit markets, (c) take into account the form in which olive oil is traded among the three spatial markets (as mentioned above, it is largely traded in bulk and it is bottled, blended or refined in the deficit market, *i.e.* Italy), and (d) consider whether producers in surplus markets have alternative market outlets when faced with a price crash in the deficit market.

Here, to identify the causal markets we conducted Granger (1969) causality tests for the time series of the rates of price changes. Table 5 presents the results. For both extra virgin and lampante olive oil the test suggested that the causal order flows uni-directional from IT to ES and GR and from ES to GR. It appears, therefore, that the olive oil importer (IT) among the three countries is the causal market leading price changes in ES and in GR. Spain (the main producer and exporter), however, leads price changes in Greece.

A positive price shock in Italy (possibly because of shortage in domestic supply) will increase import demand for extra virgin olive oil in both Spain and Greece. Given a less than perfectly elastic supply in the short run, the price of the commodity in the surplus markets will tend to rise. The extent to which a negative price shock in the importing country (possibly because of ample domestic production) will be transmitted to Spain and Greece will depend on whether: (a) producers in the exporting countries have alternative market outlets, and (b) blenders in Italy keep importing large quantities of virgin olive oil from Spain and Greece because of its taste profile. With regard to (a), Spain has a sizable share of 18% in the world exports of olive oil and, therefore, access to alternative market outlets. With regard to (b), firms in oligopolistic industries (such as the olive oil bottling and blending industry in Italy) often use product differentiation as a tool for market segmentation (*e.g.* Sexton *et al.*, 1991; EC, 2001). Hence, they may be reluctant to alter blends even when domestic supply of olive oil becomes cheaper. When conditions (a) and/or (b) hold, prices of virgin olive oil in Spain and in Greece will not fall together with the price of this commodity in Italy. The empirical finding, therefore, that a Gumbel copula describes price dependence for the pairs IT-ES and IT-

Table 5. Granger causality tests[(1)]

Null hyphothesis price changes in *i* do not cause price changes in *j* (*i*,*j* = ES,IT,GR)		Extra virgin		Lampante	
i	*j*	F-Statistic	*p*-value	F-Statistic	*p*-value
GR	ES	0.709(1)	0.401	1.315(2)	0.272
ES	GR	13.902(1)	0	19.842(2)	0
IT	ES	10.498(1)	0.002	12.567(1)	0
ES	IT	1.315(1)	0.254	1.228(1)	0.270
GR	IT	0.009(1)	0.923	0.318(1)	0.574
IT	GR	9.216(1)	0.003	35.204(1)	0

[(1)] The lags, appearing in parentheses, have been selected using the BIC criterion. Prior to conducting the Granger causality tests the series of price changes have been subjected to stationarity (ADF) tests. In all cases the null (non stationarity) has been strongly rejected.

GR is likely to be consistent with underlying market dynamics. Also, the empirical finding that the symmetric *t*-copula describes price co-movement in Spain and in Greece may simply reflect the fact that both countries serve as a huge input to the blending/bottling industry in Italy.

Since positive price shocks in Italy are transmitted to Greece and Spain, virgin olive oil blenders/bottlers in those two countries are likely to experience an increase in their costs when there is a shortage in Italy. Also, consumers in Spain and Greece are likely to face higher prices for virgin olive oil. Primary producers of virgin olive oil in the surplus markets, however, are likely to benefit from higher prices in the deficit market. When there is an ample supply in Italy, however, blenders/botlers, consumers, and primary producers in the two exporting countries are not likely to be affected.

Turning now to lampante olive oil markets, the Gumbel copula for the pair IT-ES suggests that extreme positive price shocks from Italy are transmitted to Spain, but extreme negative shocks are not. This appears to make sense given that most refiners are located in Italy, while the importance of lampante in total olive oil production of the country is relatively small (its share is 24%). To utilize fully their production capacity and to achieve economies of scale, refiners in Italy may have to keep importing lampante olive oil from Spain (the main producer) even when prices in Italy fall. The finding that the same copula family (Gumbel) best describes price co-movements in Italy and Spain for the two olive oil grades studied here (extra virgin and lampante), both characterized by considerable quality differentiation, is quite interesting; we conjecture that a similar (*i.e.* Gumbel) price dependence pattern may be relevant for other olive oil grades (such as the virgin or the refined) as well. However, these grades have not been considered here due to the lack of data.

The *t*-copula for the pair IT-GR indicates that both extreme positive and extreme negative shocks in Italy are transmitted to Greece with the same intensity. As noted above, lampante olive oil is an important input for the Italian refining/bottling industry. This grade, however, constitutes only a small part of olive oil production in Greece. Bottlers/refiners in Italy cannot rely on Greek exports of lampante to fully utilize their production capacity or to exploit economies of scale. They appear to have no reason to keep importing lampante olive oil from Greece when prices in the domestic market decrease. The symmetric price co-movement, therefore, appears to be consistent with the residual nature of lampante olive oil production in Greece.

The Gumbel copula for the pair ES-GR indicates that extreme positive shocks from Spain are transmitted to Greece, but extreme negative shocks are not. This statistical result appears to be counter-intuitive and difficult to interpret. Given the residual nature of lampante olive oil production in Greece and the high share of this grade in Spain, a symmetric price co-movement would be expected.

Discussion

Spatial price interrelationships have considerable interest for both researchers and policy makers since smooth transition of price shocks across geographically separated markets is a necessary condition for economic efficiency. At the EU level, the European Commission has pursued vigorously the goal of the integration of national markets over the last 30 years through a number of initiatives, policies, and programs.

In this context, the objective of the present work has been to investigate price interrelationships in the principal EU olive oil markets (Spain, Italy, and Greece). This objective has been pursued using copulas. The statistical tool of copulas offers considerable flexibility by dispensing with the need to make any specific assumptions about the joint distribution of prices at the different spatial markets and it is especially suitable for modeling dependence during extreme market events like booms or crashes.

According to the empirical results, over the period 2002 to 2012 there has been a variety of degrees and intensities of price co-movement in the three geographically separated markets. Depending on the market pair and the olive oil grade considered, Kendall's tau (the rank-based measure of overall dependence) ranged from 0.285 to 0.616, indicating that the tendency of prices to co-move was not particularly high. This result can be, to a certain extent, attributed to the presence of transaction costs in international trade. These tend to differ among countries because they use non tradable inputs, which may create a wedge (*e.g.* EC, 2001). Therefore, measures of overall price dependence are not expected to take very large values (*i.e.* close to 1). In two out of the six market pairs studied, tail dependence was symmetric, while for the other four pairs tail dependence was asymmetric; prices boomed together but they did not crash together. This was especially true for prices in Italy and Spain, which are by far the most important players in the EU olive oil market.

To explain the estimated price dependence patterns and to elaborate about their potential implications for primary producers, processors, and final consumers, we relied on information about the causal markets, about the form in which olive oil is traded, as well as about the location and the structure of the bottling/blending and refining industry. It appears that the empirical results are generally consistent with economic theory and the particular characteristics of the markets examined. The relatively low overall degree of dependence, and, more importantly, the evidence in favor of asymmetric price co-movements, suggest that the three principal EU olive oil markets cannot be thought of as one great pool. In this regard, the findings of the present work are in line with those of Serra *et al*. (2006), who reported evidence of asymmetric price transmission in four major EU pork markets, and Fousekis (2007), who found considerable segmentation in 15 geographically separated markets of the EU.

Finally, it is important to note that the Gaussian copula family turned out to be irrelevant for all six price pairs analyzed. This implies that empirical investigations relying on the assumption of multivariate normality for the price processes in the major EU olive oil markets could probably suffer from misspecification.

As with all similar previous empirical works on price transmission, the present study relies on bivariate copulas. Future works may consider multivariate copulas. Certain progress towards developing and implementing multivariate copulas models has been made recently by Czado *et al*. (2012). For this reason, further research on this elaborate topic is certainly warranted.

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