Price dependence and asymmetric responses between coffee varieties

Athanassios Stavrakoudis* Dimitrios Panagiotou†

Abstract

The objective of this paper is to assess the degree and the structure of price dependence between four different coffee varieties of the Arabicas and Robustas qualities. This is pursued using the statistical tool of copulas and monthly price data for the period 2006–2015. The empirical results indicate: (i) price booms and price crashes are transmitted with different probabilities in five out of six pairs of different coffee varieties, indicating asymmetric price dependence during extreme market upswings/downswings, and (ii) price increases are transmitted faster and more fully than price decreases, since in every pair examined in this study, the upper tail dependence coefficient is higher than the lower tail dependence coefficient. According to the results, coffee producers are more likely to see coffee prices of different varieties of the same and different quality to boom rather than crash together.

Keywords: coffee qualities; price dependence; price asymmetry; copula.
JEL classification: Q13, C22, C32, F15.

1. Introduction

Coffee is a drink brewed from the seeds of the Coffea genus.[1] As a world commodity, coffee is second only to oil. Coffee is mainly produced by developing countries. A large part of the agricultural sector in these economies is involved in the production as well as in the industrial procession of coffee (Talbot, 2004). Economic policies and structural reforms of coffee production and trade are of major importance for many countries in Southern America, Africa and Southern Asia (Russell et al., 2012). Furthermore, political aspects of "coffee policies" are not to be ignored as well (Paige, 1997) since the commodity of coffee is mainly produced by politically unstable countries that suffered dictatorships and political mismanagement for years. On the other hand, coffee production is related to various environmental problems connected with deforestation and land misuse. Sustainable agricultural methods and environmental friendly production and procession might help farmers and workers in the coffee producing countries (Kilian et al., 2006).

In 1989, the International Coffee Agreement (ICA) (Akiyama and Varangis, 1990; Ponte, 2002) broke down. As a result, market liberalization policies have allowed

*Assistant Professor at the Department of Economics, University of Ioannina, Ioannina, Greece. *Email*: astavrak@uoi.gr

†Assistant Professor at the Department of Economics, University of Ioannina, Ioannina, Greece. *Email*: dpanag@cc.uoi.gr

producing countries to abandon centralized planning of coffee production levels (Bacon et al., 2008). Hence, coffee production is not regulated by any state or international organization and one can claim that it is a free market regulated mainly by private interests. The market liberalization in several coffee producing countries allowed several researchers to test the Law of One Price (LOP) hypothesis. Under the LOP assumption it is expected that the commodity of coffee (or any other commodity market) is integrated enough to allow price co-movements without asymmetries. However, there is some evidence of the opposite fact. Ghoshray (2009) found evidence of asymmetries in price adjustment between different coffee milds.

Coffee quality affects sensory preferences of coffee consumers (Walsh et al., 2011; Yoon and Park, 2012). There are four different coffee varieties: "Colombian Arabicas milds" (CO), "Brazilian and other natural Arabicas" (BN), "Other mild Arabicas" (RO) and Robustas (RO).[2] The first three, namely Colombian, Brazilian and Others, are of the Arabicas quality. Arabicas coffee beans are considered to be of higher quality than Robustas. Figure 1 displays the main coffee producing countries.

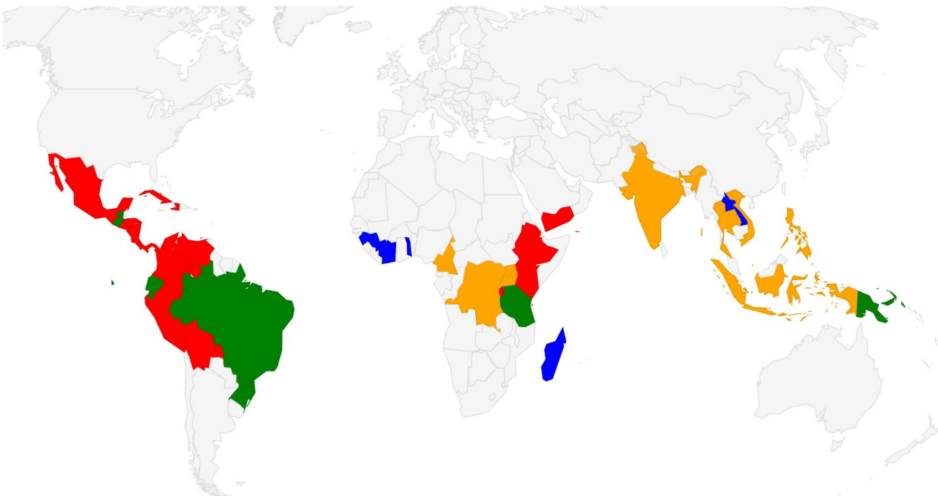

Figure 1: Coffee producing countries across the globe. Only countries with at least 0.05% of the total world production are shown. Data refer to 2014 production as provided by ICO web site (`http://www.ico.org`). Countries have been coloured as follows: Red for Arabicas milds, green for mixed products but mainly Arabicas, blue for Robustas and orange for mixed products but mainly Robustas.

Coffee prices are strongly determined by the quality of coffee (Donnet et al., 2008; Wilson and Wilson, 2014) and have shown considerable volatility in the past. Coffee production is relatively sensitive to weather conditions while coffee consumption has relative inelastic demand. A recent research on this topic (Ubilava, 2012) has revealed that El Niño Southern Oscillation (ENSO) influences coffee prices. Moreover, there is strong evidence that price dynamics have non-linear characteristics and there is evidence of asymmetries in price transmission at the farm/wholesale/retail levels (Mehtaa and Chavasb, 2008).

In addition, as with many other primary commodities, the global coffee market has been related by high volatility. Several sectors of the food industry are sensitive to prince transmission processes along the production, manufacturing and retail chains (Bakucs et al., 2014; Vavra and Goodwin, 2005) There is cumulative evidence that price transmissions can be asymmetric in many cases and that these asymmetries can be affected by several economic factors. Cointegration and meta-regression analysis have been routinely applied in the past to test for asymmetric price transmissions in a variety of commodities (Frey and Manera, 2007). There is strong evidence in the literature that several type of asymmetries exist and various econometric models can capture special sub-cases of asymmetries under certain conditions (Bakucs et al., 2014; Frey and Manera, 2007; Meyer and Cramon-Taubadel, 2004; Rapsomanikis et al., 2006; Swinnen and Vandeplas, 2014).

Despite coffee's significant importance as a commodity, most of studies have been carried out considering aggregate commodity prices of the two coffee qualities, namely Arabicas and Robustas. The objective of this study is to empirically examine the nature of price dependence between different qualities of coffee. To examine such possible dependencies we utilized the copula methodology (Joe, 2014; Nelsen, 2007). Copulas are a useful tool in order to investigate bivariate interdependencies of economic data (Joe, 2014; Meucci, 2011; Nelsen, 2007; Patton, 2012). More specifically, copulas are used to model the joint behavior of random variables during extreme market events, making it possible to assess whether prices move with the same intensity during market upswings and downswings. If prices boom and crash together, there is no evidence of asymmetric price dependence, and this is an indicator of a well functioning market. If prices in different markets do not boom but crash together (and vice versa), then there is evidence of asymmetry in the nature of price dependence. A significant advantage of copulas is that they allow the joint behavior of random processes to be modeled independently of the marginal distributions, providing this way considerable flexibility in empirical research (Joe, 2014; Patton, 2012). It has to be noted that coffee quality affects sensory preferences of coffee consumers (Walsh et al., 2011; Yoon and Park, 2012).

Copulas are an approach with many practical applications during past years (Patton, 2012; Trivedi and Zimmer, 2005). For example, oil prices and stock market indices have been shown to have direct linkages (Sukcharoen et al., 2014). It has been also hypothesized that food prices are connected to oil prices. Recent investigations with copula based methodologies have supplied evidence towards these hypothesis (Reboredo, 2011, 2012). It appears that in most recent years the price interdependence is stronger that the more past years (Reboredo, 2012). Very recently copula based models have been applied in agricultural research to investigate price dependencies (Emmanouilides and Fousekis, 2015; Panagiotou and Stavrakoudis, 2015).

The present work is structured as follows: Section 2 contains the methodology. Section 3 presents the data, Section 4 the empirical models, and Section 5 results and discussion. Section 6 offers conclusions.

2. Methodology

Copula theory dates back to Sklar (1959), but only recently copula models have realized widespread application in empirical models of joint probability distributions (see Joe (2014); Nelsen (2007) for more details). The 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.[3] As long as the marginal distributions are continuous, a unique copula is associated with the joint distribution, H, and is described in equation (1). This function constitutes a form of the principal result of copula theory (Sklar's theorem). It is obtained as:

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

Similarly, given a two-dimensional copula, $C(u_1, u_2)$, and two univariate distributions, $H_1(x)$ and $H_2(x)$, equation 1 is a two-variate distribution function with marginals $H_1(x)$ and $H_2(x)$, whose corresponding density function can be written as:

$$h(x, y) = c(H_1(x), H_2(y))h_1(x)h_2(y), \tag{2}$$

where the functions h_1 and h_2 are the densities of the distribution functions H_1 and H_2 respectively.

The density function of the copula, c, given its existence, can be derived using equation 1 and marginal density functions, h_i:

$$c(u_1, u_2) = \frac{h(H_1^{-1}(u_1), H_2^{-1}(u_2))}{h_1(H_1^{-1}(u_1))h_2(H_2^{-1}(u_2))} \tag{3}$$

A rank based test of functional dependence is Kendall's τ. It provides information on co-movement across the entire joint distribution function, both at the centre and at the tails of it. It is calculated from the number of concordant (P_N) and disconcordant (Q_N) pairs of observations in the following way:

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

Often though, information concerning dependence at the tails (at the lowest and the highest ranks) is extremely useful for economists, managers and policy makers. 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

$$\lambda_U = \lim_{u \uparrow 1} prob(U_1 > u | U_2 > u) = \lim_{u \to 1} \frac{1 - 2u + C(u, u)}{1 - u} \tag{5}$$

$$\lambda_L = \lim_{u \downarrow 0} prob(U_1 < u | U_2 < u) = \lim_{u \to 0} \frac{C(u, u)}{u} \tag{6}$$

where, given the random vector (X,Y) with marginal distribution, U_1 for X (resp. U_2 for Y), λ_U measures the probability that X is above a high quantile given that Y is also above that high quantile, while λ_L measures the probability that X is below a low quantile given that Y is also below that low quantile. In order to have upper or lower tail dependence, λ_U or λ_L need to be strictly positive. Otherwise, there is upper or lower tail independence. Hence, the two measures of tail dependence provide information about the likelihood for the two random variables to boom and to crash together. For example, in our work, positive upper and zero lower tail dependence estimates would provide evidence that big increases in wholesale prices are matched at the retail level, whereas extreme negative shocks at the wholesale level are less likely to be transmitted to the retail level.

In this study we consider a range of bivariate copula specifications of elliptical or Archimedean families. Table 1 presents the copulas under consideration in our study, their respective dependence parameters, their relationship to Kendall's τ as well as to λ_U and λ_L (upper and lower dependence coefficients). From the elliptical copulas, the Normal copula is symmetric and exhibits zero tail dependence. Thus, 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). From the one parameter Archimedean copulas, the Clayton copula exhibits only left co-movement (lower tail dependence). The Gumbel and the Joe copulas exhibit only right co-movement (upper tail dependence). The Frank copula has zero tail dependence. From the two- parameter Archimedean copulas, the Gumbel-Clayton and the Joe-Clayton allow for potentially asymmetric upper and lower co-movement. The Joe-Gumbel exhibits only right co-movement while the Joe-Frank exhibits zero tail dependence.

Copula family selection was performed with the use of Clarke test (Clarke, 2007). The scores from all pairwise comparisons of the ten copula families considered in this study are presented in Table 5. The Cramer-von-Mises (CvM) procedure for goodness of fit was used as the decisive criterion, regarding the selection of the appropriate copula family, where the Clarke test did not produce a clear choice.

Results were obtained with the maximum pseudo-likelihood (mpl) estimation method and the employment of the L-BFGS-B optimization algorithm (Byrd et al. (1995); Nash (2014); Nash and Varadhan (2011)) We allowed up to 100,000 iterations in order to achieve convergence. The selected copulas with their associated parameters are presented in Table 6. The asymptotic distributions of the copula parameters and the dependence measures, such as the Kendall's τ and the tail coefficients, were approximated using re–sampling methods. We performed 20,000 repetitions.

Goodness of fit tests for the selected copulas were performed using both the CvM test and the Kolmogorov-Smirnov (KS) test (Berg (2009); Genest et al (2013); Genest et al. (2009); Kojadinovic et al. (2011)).

Constancy of copula over time was tested with the use of the Busetti and Harvey (2011) test.

All estimations, testing, and resampling in this study have been carried out using R (version 3.1.2, R Core Team (2014)) and packages provided (Brechmann and Schepsmeier (2013); Ghalanos (2014); Yan (2007)).

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

Copula	**Parameters**	**Kendall's tau**	**Tail dependence** λ_L, λ_U
1 Gaussian (N)	$\theta \in (-1, 1)$	$\frac{2}{\pi}\arcsin(\theta)$	(0,0)
2 Student-t (t)	$\theta \in (-1, 1)$ $\nu > 2$	$\frac{2}{\pi}\arcsin(\theta)$	$2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{\frac{1-\theta}{1+\theta}})$, $2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{\frac{1-\theta}{1+\theta}})$
3 Clayton (C)	$\theta > 0$	$\frac{\theta}{\theta+2}$	$(2^{\frac{-1}{\theta}}, 0)$
4 Gumbel (G)	$\theta \geq 1$	1- $\frac{1}{\theta}$	$(0, 2 - 2^{\frac{1}{\theta}})$
5 Frank (F)	$\theta \in R\backslash\{0\}$	$1 - \frac{4}{\theta} + 4\frac{D(\theta)}{\theta}$ with $D(\theta) = \int_0^\theta \dfrac{x/\theta}{\exp(x) - 1} \mathrm{d}\, x$	(0,0)
6 Joe (J)	$\theta \geq 1$	$1+\frac{4}{\theta^2} \int_0^1 t \log(t)(1-t)^{2(1-\theta)/\theta} \, \mathrm{d}t$	$(0, 2 - 2^{\frac{1}{\theta}})$
7 Clayton-Gumbel (BB1)	$\theta_1 > 0$, $\theta_2 \geq 1$	$1 - \frac{2}{\theta_2(\theta_1+2)}$	$(2^{\frac{-1}{\theta_1\theta_2}}, 2 - 2^{\frac{1}{\theta_2}})$
8 Joe-Gumbel (BB6)	$\theta_1 \geq 1$, $\theta_2 \geq 1$	$1+\frac{4}{\theta_1\theta_2} \int_0^1 (-\log(1-(1-t)^{\theta_1})$ $\times (1-t)(1-(1-t)^{-\theta_1}))\, \mathrm{d}t$	$(0, 2 - 2^{\frac{1}{\theta_1\theta_2}})$
9 Joe-Clayton (BB7)	$\theta_1 \geq 1$, $\theta_2 > 0$	$1+\frac{4}{\theta_1\theta_2} \int_0^1 (-(1-(1-t)^{\theta_1})^{\theta_2+1}$ $\times \frac{(1-(1-t)^{\theta_1})^{-\theta_2}-1}{(1-t)^{\theta_2-1}})\mathrm{d}t$	$(2^{\frac{-1}{\theta_2}}, 2 - 2^{\frac{1}{\theta_1}})$
10 Joe-Frank (BB8)	$\theta_1 \geq 1$, $\theta_2 \in (0, 1]$	$1 + \frac{4}{\theta_1\theta_2} \int_0^1 (-\log(\frac{(1-t\theta_2)^{\theta_1}-1}{(1-\theta_2)^{\theta_1}-1})$ $\times (1-t\theta_2)(1-(1-t\theta_2)^{-\theta_1}))\, \mathrm{d}t$	(0, 0)

Table adapted from Joe (2014) and Brechmann (2013).

3. Data

Coffee prices were obtained from the International Coffee Organization website (ICO, 2016). The data are indicator prices (monthly averages expressed in USD cents per pound) of four different coffee varieties: "Colombian Arabicas milds" (Colombian or CO), "Brazilian and other natural Arabicas" (BN), "Other mild Arabicas" (Other milds, or OM) and Robustas (RO).

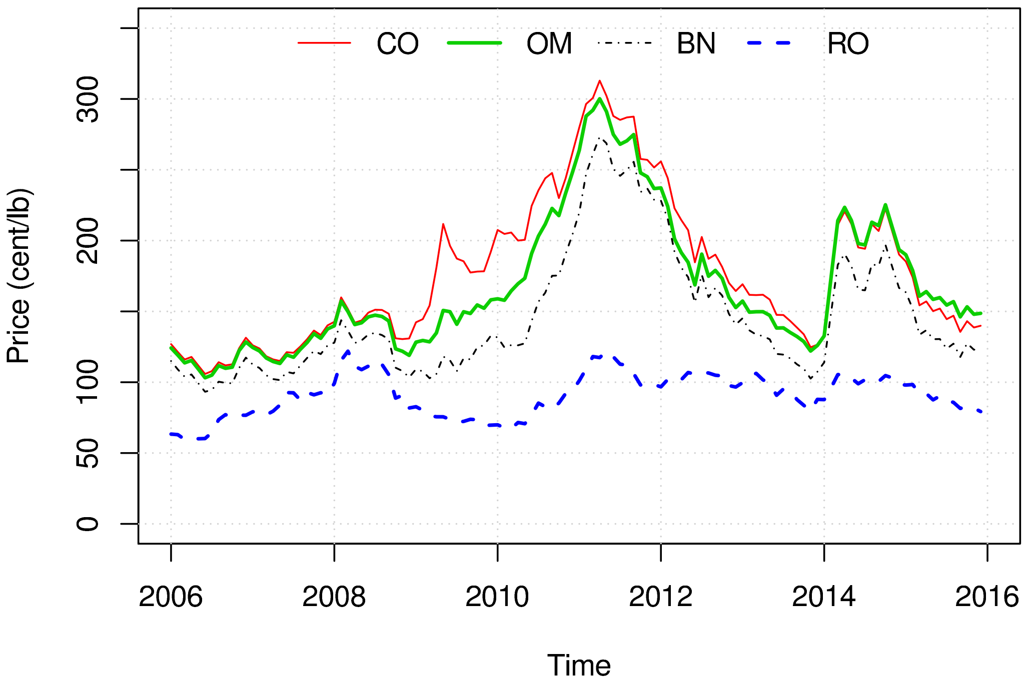

Figure 2: Price series for the four different coffee varieties.

The time period we consider in this study is from 2006:1 to 2015:12, thus taking into consideration the last decade. Figure 2 presents the time evolution of coffee prices for the four coffee qualities considered in our study. As we can observe, prices appear to move together: price increases and price decreases follow similar patterns. Colombian coffee (red continued line of Figure 2) constitutes the upper bound, which is in consistency with the fact that it is considered to be of higher quality. In contrast, lower quality Robustas (blue dashed line of Figure 2) lies on the lower bound of the four time series. BN and OM are of intermediate quality thus their time series lie between Colombian and Robustas. It must be noted that the estimation period starts shortly after the collapse of the International Coffee Agreement (ICA), when the export quotas were eliminated, and prices have since been determined under the free market conditions.

Monthly returns from coffee prices have been calculated as the percentage of value change according to the formula:

$$r_t = \frac{x_t - x_{t-1}}{x_t} \times 100 \tag{7}$$

where x_t is the indicator coffee price. These return data have been used for further estimation purposes.

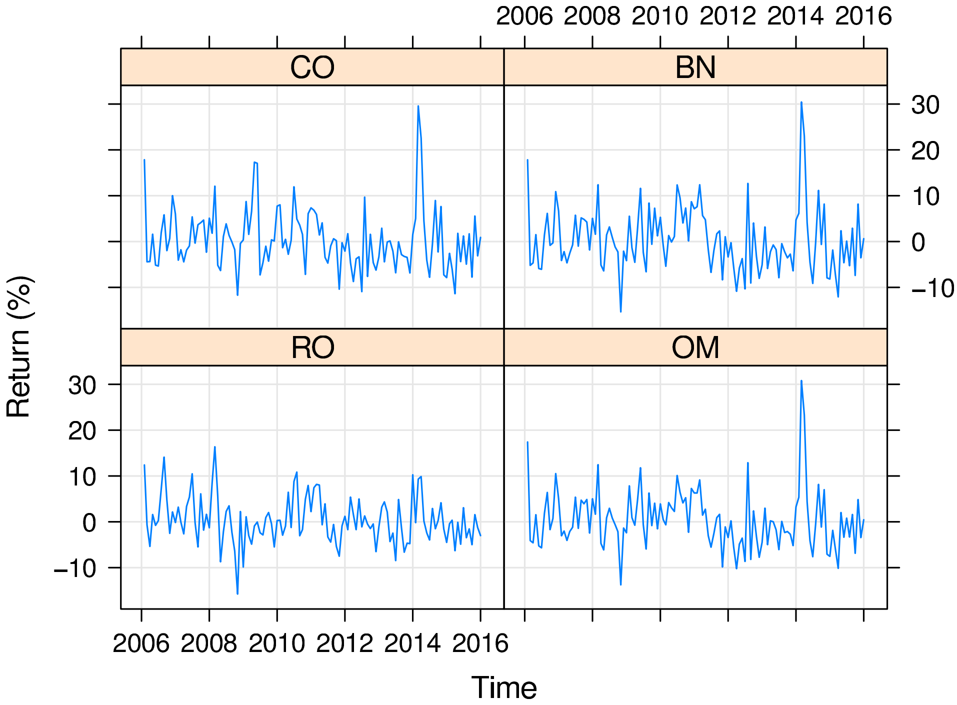

Figure 3: Time series plot of the price returns for the four different coffee varieties.

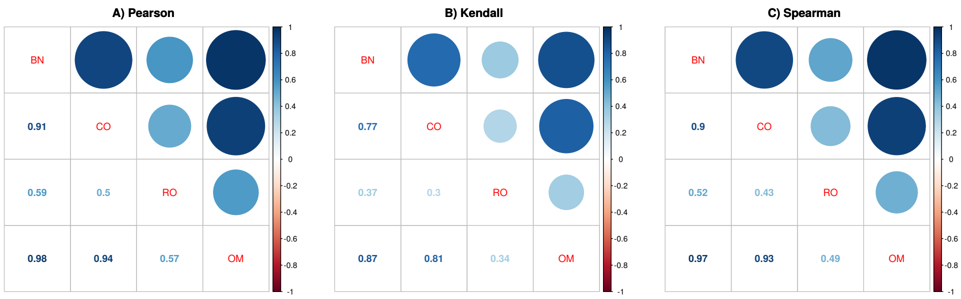

Figure 4: Correlation coefficients of coffee prices.

Figure 3 shows the time series of the return data while table 2 presents their descriptive statistics. The Kolmogorov-Smirnov (KS) and Cramer von Misses tests reject normality. The p-values of the Ljung-Box test indicate that the data are not independently distributed. From this point of view, filtering of the return data is needed.

Figure 4 presents the values of the correlation coefficients from the application of Pearson's, Kendall's and Spearman's tests. The correlation between the coffee prices of the CO, BN and OM of the Arabicas quality is quite high.

Table 2: Descriptive statistics of the coffee prices returns.

	BN	CO	RO	OM
Mean	0.429	0.430	0.414	0.478
Std. Dev.	6.974	6.698	5.152	6.412
Min	-15.346	-11.708	-15.762	-13.757
Max	30.451	29.586	16.369	30.822
Skewness	1.031	1.268	0.403	1.343
Kurtosis	5.460	6.013	3.793	7.212
KS	0.027	0.000	0.001	0.052
CvM	0.012	0.001	0.002	0.004
Q(24)	0.389	0.297	0.006	0.336
ARCH-LM	0.079	0.549	0.376	0.164

KS and CvM represent p-values for the Kolmogorov-Smirnov and Cramer von Misses test for normality respectively.
Q(24) lists the p-values of the Ljung-Box test for time series independence taking into consideration 24 lags.
ARCH-LM lists the p-values of the autoregressive conditional heteroskedasticity-Lagrange multiplier test, also using 24 lags.

4. Empirical models

A three step, semi-parametric approach has been applied for the empirical part of this article as proposed by Chen and Fan (2006):

1. An Autoregressive Moving Average – Generalized Autoregressive Conditional Heteroskedasticity Model is fit to the rates of price change for each of the series.

2. The standardized residuals are used to calculate the respective empirical distribution functions, copula with range in (0,1).

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

The semi-parametric approach exploits the fact that the copula and the margins can be estimated separately using potentially different methods. The Canonical ML copula estimator is consistent but less efficient relative to the fully parametric one. Hence, the asymptotic distributions of the copula parameters and the dependence measures, such as the Kendall's τ and the tail coefficients, are approximated using resampling methods (Choroś et al. (2010); Gaißer et al. (2010)).

To obtain the filtered rates of price change, an ARMA(2,1)-GARCH(1,1) model has been fitted to the rates of price change. ARMA with GARCH errors were estimated with rugrach package Ghalanos (2014). The obtained residuals from each of the ARMA(2,1)-GARCH(1,1) model were standardized and used to calculate the copula data on (0,1). Table 3 presents the p-values produced from the application of the Ljung-Box (Q) and the autoregressive conditional heteroskedasticity–Lagrange multiplier (ARCH–LM) tests to the filtered data at various lag lengths. The obtained

Table 3: p-Values of Lung-Box (Q) and ARCH-LM tests on the residuals obtained by ARMA(2,1)-GARCH(1,1) models. Lag order is indicated in parentheses.

	BN	CO	RO	OM
Q(1)	0.622	0.612	0.699	0.138
Q(12)	0.753	0.669	0.994	0.764
Q(24)	0.772	0.882	0.670	0.699
ARCH-LM (1)	0.040	0.019	0.519	0.004
ARCH-LM (12)	0.798	0.549	0.011	0.380
ARCH-LM (24)	0.869	0.947	0.006	0.696

Table 4: Busetti-Harvey's test results for copula stability.

pair/τ	0.1	0.3	0.5	0.7	0.9
BN/CO	0.857	0.617	0.399	0.696	0.170
BN/RO	0.595	0.633	0.355	0.434	0.502
BN/OM	0.671	0.495	0.379	0.496	0.441
CO/RO	0.505	0.944	0.480	0.435	0.524
CO/OM	0.424	0.612	0.428	0.580	0.192
RO/OM	0.422	0.659	0.381	0.549	0.608

The critical values are 0.743, 0.461 and 0.347, at the 1, 5 and 10 per cent levels of significance, respectively.

p-values reveal that the filtered data are free from autocorrelation and from ARCH effects.

The copula data was used in order to select the appropriate family function. Figure 5 presents the scatter-plots of the copula data for the six different pairs of coffee prices. Before proceeding with the selection of a specific functional form for the copula, we to tested for time–varying dependence of the copula, i.e. examine for the stability of the copula family. We tested for the constancy of the bivariate empirical copulas with the use of the Busetti and Harvey (2011) test. Table 4 presents the results from the Busetti-Harvey test for different quantiles (0.10, 0.30, 0.50, 0.70 and 0.90). The critical values are 0.743, 0.461 and 0.347, at the 1, 5 and 10 per cent levels of significance, respectively. The empirical values are in all cases below the five per cent critical value, suggesting that the null of constancy is consistent with the data. Hence, there is not sufficient statistical evidence for breaks and/or gradual but persistent shifts in the empirical copulas under examination.

The p-values of the CvM and the KS tests, for each copula family selected, are reported in table 6. The estimates of the p-values range from 0.1849 to 0.9679 for the CvM test, and from 0.2565 to 0.9743 for the KS test. The p-values of the CvM test as well as the KS test eliminate any ambiguity regarding the selection of the appropriate copula family.

Table 5: Clarke's test results for copula selection.

Pair/Copula	1	2	3	4	5	6	7	8	9	10
BN/CO	-3	3	-8	**6**	3	-6	5	4	0	-4
BN/RO	3	**6** (0.754)	-4	-1	-2	-7	**6** (0.964)	-3	4	-2
BN/OM	**6** (0.912)	**6** (0.472)	-6	4	3	-5	4	0	-5	-7
CO/RO	2	2	-7	2	0	-6	**6**	0	2	-1
CO/OM	-1	2	-8	**5** (0.167)	3	-5	**5** (0.172)	3	-2	-2
RO/OM	4	3	-6	3	-5	-6	**6**	1	5	-5

Numbers in first row correspond to copula families Copula families as given at table 1.
Boldface indicates copula family that gave the highest score.
Values in parentheses indicate p-value of Cramer von Misses goodness of fit test in order to discriminate between two equally scored copula families.

5. Results and discussion

Table 6 presents the selected copula families for the six pairs of coffee milds. Kendall's τ estimates range from 0.3079 to 0.8658, and are statistically significant at the 1% level. The high values of Kendall's tau between the pairs Brazilian-Colombian (0.7502), Brazilian-Others (0.8658) and Colombian-Others (0.7651) indicate the strong overall dependence between the three coffee varieties of the Arabicas quality. This can also be seen in figure 5, where the scatterplots of the copula data (ranks) reveal the strong relationship between the three pairs of the coffee beans from the Arabicas quality. Overall dependence between the coffee varieties of the Arabicas quality and the Robustas quality is not as strong.

For the BN/CO pair the Gumbel copula was selected, which points to a certain degree of asymmetry in the tails of the joint distribution. The lower tail dependence coefficient for the aforementioned copula is zero and the upper tail dependence (λ_U) coefficient is different than zero. The estimated value of λ_U is 0.8110 and is statistically significant at any reasonable level. Our results indicate that a price crash in one of the two varieties will not be associated with a price crash in the other coffee variety and vice versa. On the other hand, the probability that a price boom in one of the two varieties will be transmitted to the other is 0.8110 and is statistically different than zero. The estimated value of Kendall's τ is 0.7502, indicating a strong overall dependence.

For the pair BN/RO the Clayton-Gumbel (BB1) copula points to asymmetric tail dependence. The estimate of lower tail coefficient (λ_L) is 0.1886, while the estimated value of the upper tail coefficient (λ_U) is 0.3603. The tail dependence coefficients are statistically significant at any reasonable level. The value of λ_L suggests that with a probability of 0.1886, a strongly negative rate of price change in one of the two coffee qualities will be matched with a similarly strong negative rate of price change in the other coffee quality. On the other hand, the value of λ_U indicates that

Table 6: Copula parameter estimates for the six pairs of different coffee qualities. CvM and KS are the p-values of the Cramér–von Mises and Kolmogorov-Smirnov tests respectively. For Normal and Frank copulas one parameter is estimated (θ_1), for BB1 (Clayton-Gumbel) and t copulas two parameters (θ_1, θ_2) have been estimated. Standard errors (in parentheses) were obtained with the bootstrap method.

Pair	Copula	CvM/KS	Parameters ($\hat{\theta}$)	Kendall's τ	λ_L	λ_U
BN/CO	G	0.3230	4.003	0.7502	0.0000	0.8110
		0.4344	(0.0048)	(0.0003)		(0.0002)
BN/RO	BB1	0.9679	0.2964/1.4017	0.3787	0.1886	0.3603
		0.9068	(0.0019/0.0011)	(0.0004)	(0.0014)	(0.0006)
BN/OM	N	0.9355	0.9779	0.8658	0.0000	0.0000
		0.9743	(0.0000)	(0.0001)		
CO/RO	BB1	0.9043	0.2451/1.2871	0.3079	0.1111	0.2865
		0.9056	(0.0018/0.0010)	(0.0004)	(0.0012)	(0.0008)
CO/OM	BB1	0.1849	0.297/3.7062	0.7651	0.5328	0.7943
		0.3015	(0.0027)/(0.0059)	(0.0002)	(0.0027)	(0.0004)
RO/OM	BB1	0.6645	0.3096/1.3673	0.3667	0.1945	0.3398
		0.2565	(0.0019)/(0.0010)	(0.0004)	(0.0014)	(0.0006)

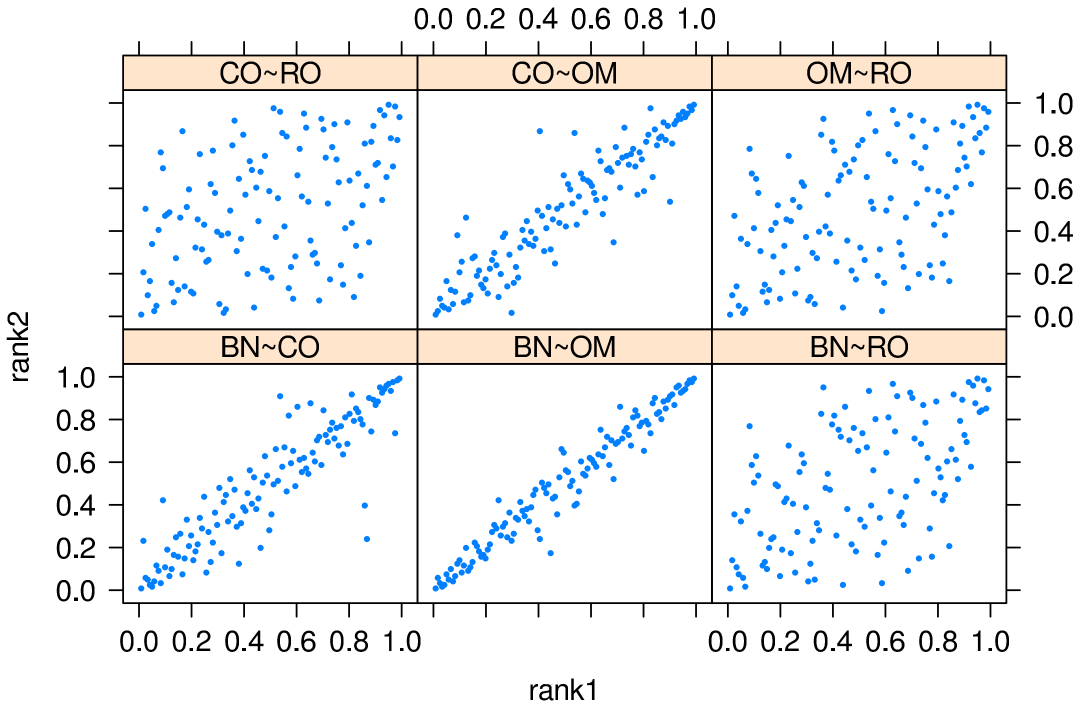

Figure 5: Scatterplots of the copula data (ranks). Data have been plotted as rank2~rank1, with rank1 on the horizontal axis and rank2 on the vertical axis respectively.

with a probability of 0.3603 BN and RO prices will boom together. The estimate of Kendall's τ is 0.3787.

The Normal copula family was selected for the pair BN/OM, indicating that the tail dependence coefficients (λ_L,λ_U) are no different than zero. Zero values for the tail dependence coefficients means that at the tails of the joint distribution of price changes, extreme market events occur independently in each margin. Thus, a price crash (boom) in the BN will not be associated with a price crash (boom) in the OM and vice versa. However, the estimate of Kendall's τ is very high (0.8658), suggesting a very strong propensity of co–movement in parts of the joint distribution other than its tails.

For the CO/RO pair the Clayton-Gumbel (BB1) copula family was chosen, which indicates that co–movements at the extremes are not equally relevant during extreme market downturns and upturns. The estimate of the lower tail coefficient (λ_L) is 0.1111, while the estimated value of the upper tail coefficient (λ_U) is 0.2865. The tail dependence coefficients are statistically significant at any reasonable level. The value of λ_L indicates that with a probability of 0.1111, CO and RO prices will crash together. On the other hand, the value of λ_U suggests that with a probability of 0.2865, a strongly positive rate of price change in one of the two coffee qualities will be matched with a similarly strong positive rate of price change in the other coffee quality. The estimate of Kendall's τ is the lowest between all pairs examined in this study. Its value is 0.3079.

For the pair CO/OM, the Clayton-Gumbel (BB1) copula family points to asymmetric tail dependence, since λ_L and λ_U assume different values. The estimate of lower tail coefficient (λ_L) is 0.5328, while the estimated value of the upper tail coefficient (λ_U) is 0.7943. The tail dependence coefficients are statistically significant at any reasonable level. The value of λ_L suggests that with a probability of 0.5328, a strongly negative rate of price change in one of the two coffee qualities will be matched with a similarly strong negative rate of price change in the other coffee quality. On the other hand, the value of λ_U indicates that with a probability of 0.7943 CO and OM prices will boom together. The estimate of Kendall's τ is 0.7651, indicating a very strong overall dependence.

For the pair RO/OM the Clayton-Gumbel (BB1) copula suggests tail asymmetry. The estimated value of lower tail dependence coefficient is 0.1945, while the estimate of the upper tail dependence coefficient is 0.3398. The tail dependence coefficients are statistically significant at any reasonable level. Their estimated values of λ_L and λ_U suggest that with a probability of 0.1945 RO and OM prices will crash together, and with a probability of 0.3398 the prices of RO and OM will boom together. The estimate of Kendall's τ is 0.3667.

Our empirical findings reveal asymmetric price dependence in five out of six pairs examined in this study, when extreme events take place in the coffee market. Tail asymmetries are stronger between the different varieties of the Arabicas quality and quite milder between the different varieties of the Arabicas quality with the coffee beans of the Robustas quality. In all cases, the probability that a price boom will be transmitted is much higher than the transmission probability of a price crash, since the upper tail dependence coefficient is higher than the lower tail dependence coefficient for every pair. The only exception is for the pair BN/OM of the Arabicas quality, where price crashes (booms) in one variety will not be associated with price crashes (booms) in the other variety. For the specific pair though, Kendall's τ is very high, suggesting that price increases and decreases in one variety were generally transmitted to the other variety, except from the very extreme ones.

In the light of the above information, price booms are more likely to affect coffee producers than price crashes, since the probability of tail co–movement during market upswings is much higher than the probability of tail co–movement during market downswings. Hence, coffee producers are more likely to see coffee prices boom together rather than crash together. In the case where coffee producers are involved in the production of both CO and BN coffee beans of the Arabicas quality, there is a zero probability of a price crash transmission between these two varieties, and the highest probability of a price boom transmission between these two varieties. Ceteris paribus, coffee producers of both Colombian and Brazilian coffee beans of the Arabicas quality are completely insulated during extreme market downswings.

6. Conclusions

Asymmetries in the transmission of price volatility have always been in the center of attention in agricultural and food economics, since this might be an indicator of economic inefficiency. Coffee as a world commodity, is second only to oil. Despite its importance as a commodity, most of studies have been carried out considering aggregate commodity prices of the two coffee qualities, namely Arabicas and Robustas. In this context, the objective of this work was to assess the nature of price dependence between four different coffee varieties when extreme market conditions prevail in the market(s).

Our empirical findings reveal evidence of asymmetric price dependence under extreme market price increases/decreases in the coffee market. More specifically:

- Price booms and price crashes are transmitted with different probabilities in five out of six pairs of different coffee varieties and/or qualities, indicating asymmetric price dependence during extreme market upswings/downswings. The only exception is the pair between the varieties of Brazilian and Other Milds of the Arabicas quality, where price crashes (booms) are not associated with price crashes (booms).

- Price increases are transmitted faster and more fully than price decreases, since in every pair examined in this study, the upper tail dependence coefficient is higher than the lower tail dependence coefficient. Hence, coffee producers are more likely to see coffee prices of different varieties of the same and different quality to boom rather than crash together.

To interpret the estimated price dependence patterns and in order to be able to speculate about their potential implications for coffee producers, some facts with respect to the production of coffee worldwide are necessary. More than 90% of coffee production takes place in developing countries and approximately 25 million small producers world- wide rely on coffee for a living. According to the results of this work, the probability that coffee producers will observe price crashes being transmitted between different varieties is quite low or zero, in five out of six pairs examined in this study. Hence, our empirical findings indicate that the producers of coffee are less vulnerable when extreme price decreases take place in the coffee industry. Since most of these producers rely on coffee for a source of income, the fact that they are somehow ”isolated” to price crashes provides policy makers with more information regarding their decision to support the income of coffee producers during periods of market turbulence.

Future research may consider multivariate copulas in order to assess price dependence in the coffee market. Furthermore, researchers can consider fair trade coffee producers since seventy–seven per cent of fair trade coffee production comes from Latin American countries, where higher quality Arabicas coffee beans are produced.

Acknowledgements

Authors thank Fabio Busetti for providing his Ox code for copula stability test.

Notes

[1]One coffee ”cherry” contains two seeds or ”beans”.

[2]Some studies indicate the coffee beans of the Colombian Arabicas milds, Brazilian and other natural Arabicas, Other mild Arabicas and Robustas as beans of different quality. In this study, in order to indicate the difference in quality between Arabicas and Robustas coffee beans, we will call these four different types of coffee beans as varieties.

[3]For simplicity we consider the bivariate case. The analysis, however, can be extended to a p-variate case with $p > 2$.

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