Price dependence between coffee qualities: a copula model to evaluate asymmetric responses

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Price dependence between coffee qualities: a copula model to evaluate asymmetric responses

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Abstract

The objective of this paper is to assess the degree and the structure of price dependence between different coffee qualities of the Arabica and Robusta varieties. This is pursued using the statistical tool of copulas and monthly price data for the period 1990:1–2014:12. Our results reveal evidence of asymmetric price dependence between the pairs Brazilian–Robusta, Brazilian–Others and Robusta–Others, since price booms and price crashes are transmitted with different probabilities between these pairs of coffee qualities. For the pairs Brazilian–Colombian, Colombian–Robusta and Colombian–Others there is no evidence of asymmetric price dependence. The empirical findings of this article indicate that the probability that fairtrade coffee producers will see a price crash in the Robusta variety being transmitted to the coffee qualities of the Arabica variety is either zero or much lower than the probability of the transmission of a price boom.

Keywords: coffee–qualities; price dependence; copula; fairtrade

JEL classification: Q13, C14, F15.

1 Introduction

Coffee is a drink brewed from the seeds of the Coffea genus.[1] It is one of the major commodities produced mainly by developing countries. As a world commodity, coffee is second only to oil. Economic policies and structural reforms of coffee production and trade are of major importance in many countries in Southern America, Africa and Southern Asia (Russell et al., 2012). A large part of the agricultural sector in these economies is involved in coffee production and its industrial procession (Talbot, 2004). Political aspects of "coffee policies" are not to be ignored in coffee industry (Paige, 1997) as this commodity is mainly produced in 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 production countries (Kilian et al., 2006).

After 1989 the International Coffee Agreement (ICA) (Akiyama and Varangis, 1990; Ponte, 2002) broke down and since then market liberalization policies had allowed producer countries to abandon centralized planning of coffee production levels (Bacon et al., 2008). Coffee production is not regulated by any state or international organization, we can say that it is a free market and it is regulated only by private interests. The brake up of ICA and market liberalization steps that followed in several coffee producing countries let several researchers to test the Low of One Price (LOP) hypothesis. Under this assumption it is expected that 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. Recent research (Ghoshray, 2009) applying threshold autoregressive (TAR) or momentum threshold autoregressive (M-TAR) models indicated asymmetries in price adjustment between different coffee milds.

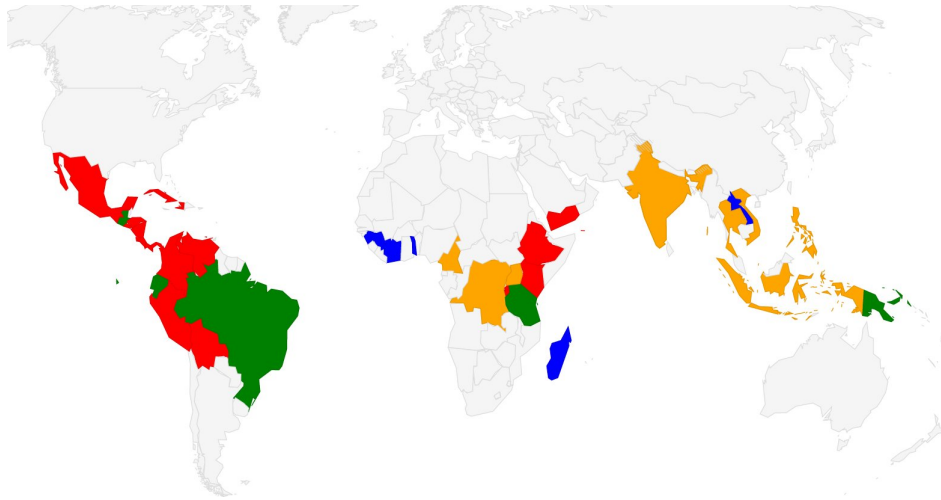[1]One coffee "cherry" contains two seeds or "beans."

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.

As with many other primary commodities, the global coffee market has been defined 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).

Farming methods affect coffee quality and of course coffee prices are strongly determined by quality of coffee (Donnet et al., 2008; Wilson and Wilson, 2014). Coffee prices showed considerable volatility in the past. Coffee production is relatively sensitive to weather conditions while coffee consumption has relative inelastic

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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 at price transmissions at the farm/wholesale/retail levels (Mehtaa and Chavasb, 2008).

Despite coffee's significant importance as a commodity, most of studies have been carried out considering aggregate commodity prices of the two coffee varieties, 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).

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 in-

terdependence 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.[2] 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:

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

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

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 dis-concordant (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.

This study considers a range of bivariate copula specifications. All of them are

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members of the elliptical copulas and Archimedean copulas, since they permit considerable flexibility in capturing price dependence between different cuts of beef between wholesale and retail level in the US beef industry. Elliptical and Archimedean copulas are the two of the most commonly used copula families. The elliptical copulas that we evaluate are the Gaussian (or Normal) and Student–t. Among the one parameter Archimedean copulas we consider there are the Clayton, Gumbel, Frank, and Joe. Clayton-Gumbel, Joe-Gumbel, Joe-Clayton and the Joe-Frank are among the two-parameter Archimedean copulas we examine.

Table 1 presents the copulas (Brechmann and Schepsmeier, 2013) 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 Gaussian 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.

Recently, dynamic or time-varying copula models have been applied in order to investigate time-varying dependence structure (Manner and Reznikova, 2012; Reznikova, 2012). In this study we tested for time-varying dependence using Kendall's τ estimation over a rolling window or the price time series over 36 periods (month by month).

Table 1: Copulas functions, parameters, kendall's τ, tail dependence

Copulas	Parameters	Kendall's τ	Tail dependence (λ_L, λ_U)
Gaussian	$\theta \in (-1, 1)$	$\frac{2}{\pi}\arcsin(\theta)$	$(0,0)$
Student - t	$\theta \in (-1, 1)$ v¿2	$\frac{2}{\pi}\arcsin(\theta)$	$2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{\frac{1-\theta}{1+\theta}})$, $2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{\frac{1-\theta}{1+\theta}})$
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	$\theta \in R\backslash\{0\}$	$1 - \frac{4}{\theta} + 4\frac{D(\theta)}{\theta}$	$(0,0)$
Joe	$\theta \geq 1$	$1 + \frac{4}{\theta^2}\int_0^1 t\log(t)(1-t)^{2(1-\theta)/\theta}\,dt$	$(0, 2 - 2^{\frac{1}{\theta}})$
Clayton-Gumbel	$\theta_1 > 0, \theta_2 \geq 1$	$1 - \frac{2}{\theta_2(\theta_1+2)}$	$(2^{\frac{-1}{\theta_1\theta_2}}, 2 - 2^{\frac{1}{\theta_2}})$
Joe-Gumbel	$\theta_1 \geq 1, \theta_2 \geq 1$	$1 + \frac{4}{\theta_1\theta_2}\int_0^1 (-\log(1-(1-t)^{\theta_1}) {} *(1-t)(1-(1-t)^{-\theta_1}))dt$	$(0, 2 - 2^{\frac{1}{\theta_1\theta_2}})$
Joe-Clayton	$\theta_1 \geq 1, \theta_2 > 0$	$1 + \frac{4}{\theta_1\theta_2}\int_0^1 (-(1-(1-t)^{\theta_1})^{\theta_2+1} {} *\frac{(1-(1-t)^{\theta_1})^{-\theta_2}-1}{(1-t)^{\theta_2-1}})dt$	$(2^{\frac{-1}{\theta_2}}, 2 - 2^{\frac{1}{\theta_1}})$
Joe-Frank	$\theta_1 \geq 1, \theta_2 \in (0, 1]$	$1 + \frac{4}{\theta_1\theta_2}\int_0^1 (-\log(\frac{(1-t\theta_2)^{\theta_1}-1}{(1-\theta_2)^{\theta_1}-1}) {} *(1-t\theta_2)(1-(1-t\theta_2)^{-\theta_1}))dt$	$(0, 0)$

3   Data

Coffee prices were obtained from the International Coffee Organization website (ICO, 2015). The data are indicator prices (monthly averages expressed in USD cents per pound) of four different coffee qualities: "Colombian Arabicas milds" (Colombian, or Col), "Brazilian and other natural Arabicas" (Brazilian, or Bra), "Other mild Arabicas" (Others, or Oth) and Robustas (Rob). The first three, namely Colombian, Brazilian and Others, are of the Arabica variety and considered to be of higher quality. Robustas is mainly produced by African countries and it is considered to be of relatively lower quality in comparison with the Arabicas.

The time period we consider in this study is from 1990:1 to 2014:12. 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. Brazilian and Other Milds 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 shows the time series of the return data while table 2 presents their
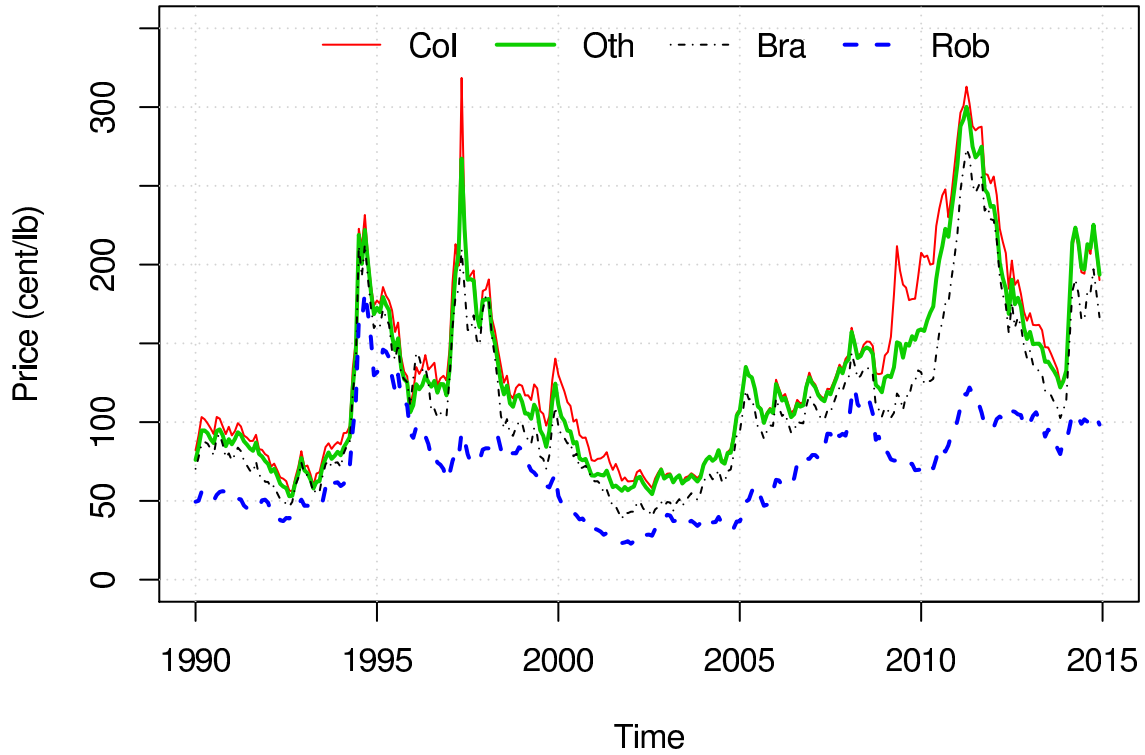
Figure 2: Plot of coffee prices (USD cents per lb).

Table 2: Descriptive statistics of the coffee prices returns (values as percentages). P-values are displayed for the Kolmogorov-Smirnov (KS) and Cramer von Misses test for normality. Q(24) lists the p-values of the Ljung-Box test for time series independence taking into consideration 24 lags. ARCH-LM lists p-values of the autoregressive conditional heteroskedasticity–Lagrange multiplier test, also using 24 lags.

	Brazilian	Colombian	Robustas	Other
Mean	0.078	0.072	0.068	0.078
Std. Dev.	1.820	1.681	1.662	1.606
Min	-3.774	-5.865	-5.423	-3.408
Max	8.948	8.862	8.005	8.513
Skewness	0.871	1.153	0.746	1.107
Kurtosis	4.899	7.314	5.454	6.117
KS	0.007	0.000	0.000	0.001
CvM	0.001	0.000	0.000	0.000
Q(24)	0.001	0.008	0.000	0.000
ARCH-LM	0.064	0.245	0.038	0.009

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.
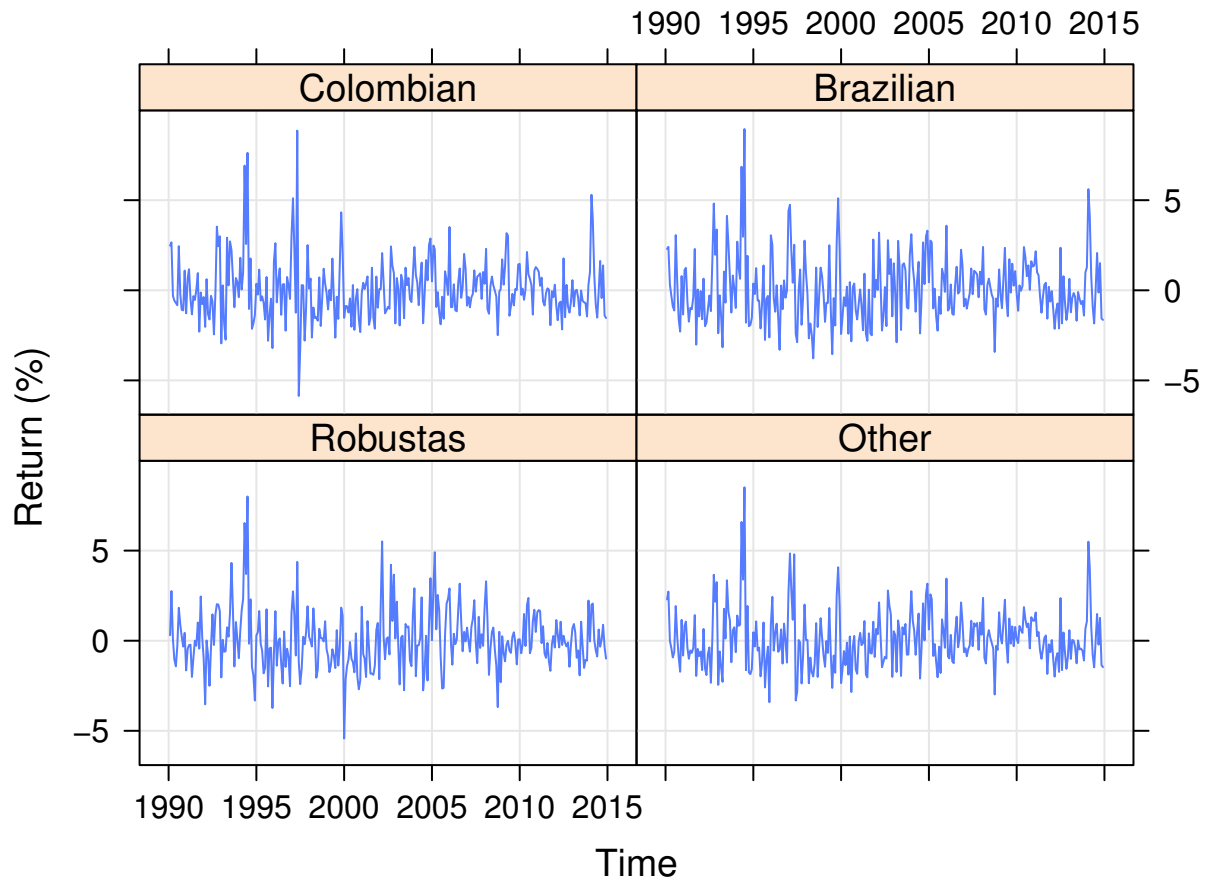

Figure 3: Plot of price returns.

Figure 4 shows the density distribution of the return data of the four coffee prices along the ideal normal distribution curve for comparison. It is evident from this graph that distribution of returns of the four coffee prices deviate from normality. This was also confirmed by examining the p-values of the Kolmogorov-Smirnov and Cramér–von Mises normality tests depicted at Table 2.

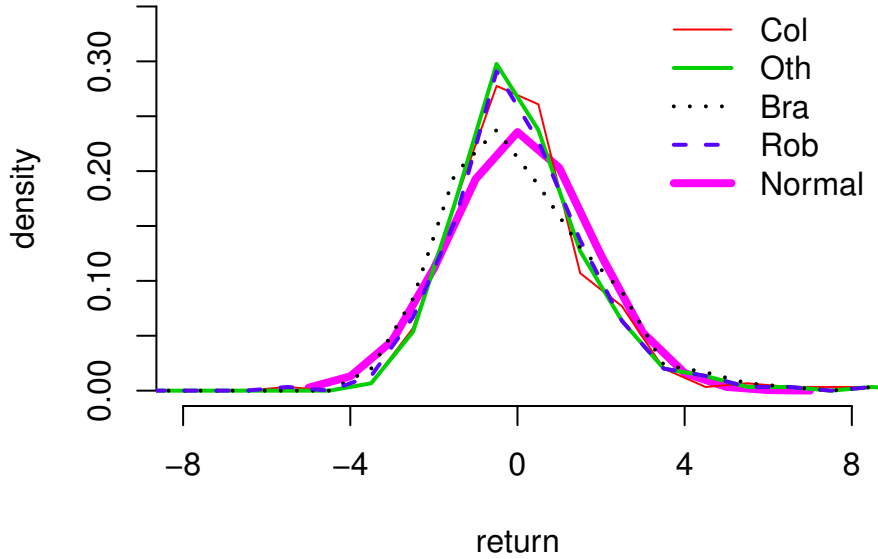Table 3 presents correlation measurements between the four coffee qualities.

Figure 4: Density plot of price returns for the four coffee qualities. corresponding line of normal distribution (think magenta line) has been computed with mean=0.074 and sd=1.692, these values were obtained from mean and standard deviation of combined price returns of the four coffee time series.

Table 3: Correlation measurement between pairs of coffee prices.

Pair	Pearson	Kendall's τ	Spearman's rho
Brazilian/Colombian	0.891	0.757	0.909
Brazilian/Robustas	0.706	0.477	0.660
Brazilian/Other	0.948	0.815	0.948
Colombian/Robustas	0.671	0.431	0.604
Colombian/Other	0.951	0.833	0.952
Robustas/Other	0.714	0.460	0.639

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 (ARMA–GARCH) 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)). All estimations, testing, and resampling in this study have been carried out using R (version 3.1.2, R Core Team (2014)).

To obtain the filtered rates of price change, an ARMA(p,q)–GARCH(1,1) model has been fit to the rates of price change. ARMA with GARCH errors were estimated with rugrach package developed by Ghalanos (2014). We allowed for maximum order of three for the ARMA model. Model selection was based on the Akaike Information Criterion. The obtained residuals from each of the ARMA(p,q)-GARCH(1,1) model were standardized (filtered data) and used to calculate the copula data on (0,1). Figure 5 presents the scatter-plots of the copula data for the six different pairs of coffee prices. Table 4 presents the selection of the best fitted ARMA(p,q)-GARCH(1,1)

Table 4: Fitted ARMA(p,q)–GARCH(1,1) models of coffee price returns and test statistics of the residuals. First row (p,q) lists the ARMA order. Second row Q(1) lists the p-values of Lung–Box test with lag=1. Third row Q(5/24) lists the same but with lag=5 for models where $p+q = 1$ and lag=24 where $p+q = 5$. Rows ARCH(3) and ARCH(7) list p-values of the ARCH-LM test with 3 and 7 lags respectively. The last row lists the selected distribution of the residuals: snorm is the skewed normal distribution, sstd is the skewed student t distribution and ged is the generalized error distribution.

	Brazilian	Colombian	Robustas	Other
(p,q)	(1,0)	(0,1)	(3,2)	(2,3)
Q(1)	0.219	0.509	0.773	0.505
Q(5/24)	0.093	0.212	0.300	0.877
ARCH-LM (3)	0.660	0.439	0.980	0.053
ARCH-LM (7)	0.864	0.750	0.653	0.314
Distribution	snorm	sstd	ged	snorm

model for each of the series as well as 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 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. Copula family selection was performed with CDVine package (Brechmann and Schepsmeier, 2013) based on AIC/BIC criteria (Dißmann et al. (2013); Jordanger and Tjøstheim (2014); Manner (2007)). The same copula families were selected for all pairs in both criteria.

Goodness of fit was performed using both the CvM test and the KS test. (Berg (2009); Genest and Huang (2012); Genest et al. (2009); Kojadinovic et al. (2011)). The copula package in R was employed for the CvM and the KS procedures (Hofert et al. (2014); Yan (2007)). Results were obtained with the maximum pseudo-likelihood (mpl) estimation method, and the dependence parameters were estimated using the L-BFGS-B optimization algorithm (Byrd et al. (1995); Nash (2014); Nash and Varadhan (2011)), while allowing up to 100,000 iterations to achieve conver-

gence.

The Cramer-von-Mises and the Kolmogorov–Smirnov procedures were decisive regarding the selection of the appropriate copula family. The selected copulas with their associated parameters are presented in Table 5. The p-values of the CvM and the KS tests for each copula family selected, are also reported in the above mentioned table. The estimates of the p-values range from 0.133 to 0.779 for the CvM test, and from 0.156 to 0.884 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. The asymptotic distributions of the copula parameters and the dependence measures, such as the Kendall's τ and the tail coefficients, were approximated using resampling methods. We performed 20,000 repetitions. Figure 6 presents graphically the density plots of the copula parameter(s) as well as Kendall's τ from parametric and non-parametric 20,000 bootstrap repetitions for each one of the six pairs of coffee qualities examined in this study.

Table 5: 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 and standard deviations (in parentheses) were obtained with the bootstrap method.

Pair	Copula	CvM/KS	Parameters ($\hat{\theta}$)	Kendall's τ	λ_L	λ_U
Bra/Col	Frank	0.133/0.156	15.086	0.764	0.000	0.000
			(1.174)	(0.016)	(-)	(-)
Bra/Rob	BB1	0.794/0.841	0.284/1.579	0.446	0.214	0.449
			(0.113)/(0.091)	(0.024)	(0.101)	(0.040)
Bra/Oth	BB1	0.387/0.233	0.189/3.186	0.713	0.316	0.757
			(0.067)/(0.159)	(0.013)	(0.087)	(0.014)
Col/Rob	Normal	0.636/0.884	0.587	0.400	0.000	0.000
			(0.032)	(0.026)	(-)	(-)
Col/Oth	t-copula	0.149/0.298	0.907/5.735	0.724	0.586	0.586
			(0.008)/(1.038)	(0.012)	(0.034)	(0.034)
Rob/Oth	BB1	0.779/0.728	0.369/1.448	0.417	0.273	0.386
			(0.115)/(0.092)	(0.024)	(0.091)	(0.048)

5   Results and discussion

Table 5 presents the selected copula families for the six pairs of coffee milds. Kendall's τ estimates range from 0.400 to 0.764, and are statistically significant at the 1% level. The high values of kendall's tau between the pairs Brazilian–Colombian (0.764), Brazilian–Others (0.713) and Colombian–Others (0.724) indicate the strong overall dependence between the three coffee qualities of the Arabica variety. This can also be seen in figure 5, where the scatterplots of the copula data (ranks) between the pairs formed between the three coffee qualities of the Arabica variety reveal their strong overall relationship. Overall dependence between the coffee qualities of the Arabica variety and the Robusta variety/quality is not as strong.

For the Brazilian–Colombian pair the Frank copula was selected, implying that

both tail dependence coefficients (λ_L, λ_U) are no different than zero. This means that a price crash (boom) in one of the coffee qualities of the pair Brazilian–Colombian will not be associated with a price crash (boom) in the other coffee quality of the specific pair. The estimated value of Kendall's τ is 0.764 and is the highest among the six pairs examined in this study, indicating this way the strongest overall dependence.

For the pair Brazilian–Robusta the Clayton-Gumbel (BB1) copula points to asymmetric tail dependence. The estimate of lower tail coefficient (λ_L) is 0.214, while the estimated value of the upper tail coefficient (λ_U) is 0.449. The tail dependence coefficients are statistically significant at any reasonable level. The value of λ_L suggests that with a probability of 0.214 a strongly negative rate of price change in one of the two coffee qualities will be matched with a 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 0.449 Brazilian and Robusta prices will boom together. The estimate of Kendall's τ is 0.446.

The Clayton-Gumbel (BB1) copula was also selected for the pair Brazilian–Others. The value of the estimate for the lower tail dependence coefficient is 0.316 and the estimate for the upper tail dependence coefficient is 0.757. Both are statistically significant at any reasonable level. The estimated values for the tail dependence coefficients suggest that with a probability of 0.214 the prices of the Brazilian and Other milds will crash together and with a probability of 0.449 a strongly positive rate of price change change in either one of the two coffee qualities of the Arabica variety will be matched with a with a similarly strong positive rate of price change in the other coffee quality. The estimate of the overall dependence parameter is 0.713.

For the Colombian–Robusta pair the Normal (or Gaussian) copula family was chosen, implying that both tail dependence coefficients, λ_L and λ_U are no different than zero. This means that a crash (boom) in the price of the Colombian will not

be associated with a crash (boom) in the price of the Robusta, and vice versa. The estimate of Kendall's τ is 0.400.

For the pair Colombian–Others, the student–t copula points to symmetric tail dependence, since λ_L and λ_U take the same value. The tail dependence coefficients suggest that coffee prices of Colombian and Other milds boom and crash together with a probability of 0.586. The estimate of Kendall's τ is 0.724, indicating strong overall dependence.

For the pair Robusta–Others the Clayton-Gumbel (BB1) copula points to asymmetric tail dependence. The estimated value of lower tail dependence coefficient is 0.273, while the estimate of the upper tail dependence coefficient is 0.386. 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 0.214 Brazilian and Robusta prices will crash together and with a probability of 0.449 the prices of Brazilian and Robusta will boom together. The estimate of Kendall's τ is 0.446.

Our empirical findings reveal evidence of asymmetric price dependence between the pairs of Brazilian–Robusta, Brazilian–Others and Others–Robusta, since price booms and price crashes are transmitted with different probabilities between these three pairs of coffee qualities. On the other hand, for the pairs Brazilian–Colombian, Colombian–Robusta and Colombian–Others there is no evidence of asymmetric price dependence, since our results show that price booms (crashes) will be transmitted with the same probability. The probability price transmission is no different than zero for the pairs Brazilian–Colombian and Colombian–Robusta, and assumes the value of 0.586 for the pair Colombian–Others.

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 worldwide rely on coffee for a living. As with many other primary com-

modities, coffee has been defined by high volatility and long-term declining prices. In order to alleviate the impacts of the low coffee prices sustainable coffee production and certification have been a logical choice for many producers. Coffee is generally regarded as the leading industry for sustainability standards and certification (Reinecke et al., 2012). One of the pioneers in sustainability certification is Fairtrade. Fairtrade coffee production has to adhere to fairtrade standards. There are two types of generic standards: one for small producers and another for workers on plantations and in factories(Kilian et al., 2006). The first one applies to small-property owners organized into cooperatives or other types of organizations with a democratic and participatory structure. The second one applies to organized workers whose employers pay decent salaries, guarantee them the right to join unions and provide lodging when relevant. Fairtrade's production has relied heavily on Latin American sources, with an estimated 77 per cent of fairtrade coffee production coming from Latin American countries, where higher quality Arabica coffee is produced.[3] In Colombia, Peru, and Nicaragua fairtrade represents 20 per cent or more of domestic production. At the same time, sales of fairtrade coffee are still experiencing growth, making it this way quite vulnerable to extreme events of price volatility.

Our empirical findings indicate that the price of the Colombian mild (highest Arabica quality) and Robusta price will neither crash nor boom together. This means that the probability that an extreme decrease in the prices of the Robusta quality will cause an extreme reduction in the prices of the Colombian quality of coffee is no different than zero. The Colombian quality belongs to the Arabica variety which is mainly produced in Latin America where the majority of faitrade coffee is produced.

On the other hand, the probability that a price crash in the price of the Robusta will cause a crash in the price of the Brazilian and the price of the Other milds of the Arabica variety is lower than the probability of the transmission of a price

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[3]As Kilian et al. (2006) point out for coffee certification the price is always a function of both quality and certification, where quality can be seen as a more basic prerequisite.

boom between the pairs formed by these coffee qualities. This means that fairtrade coffee producers of these two qualities of the Arabica variety will see a price increase happening with much higher probability than a price decrease when extreme market conditions occur in the production of the Robusta coffee quality.
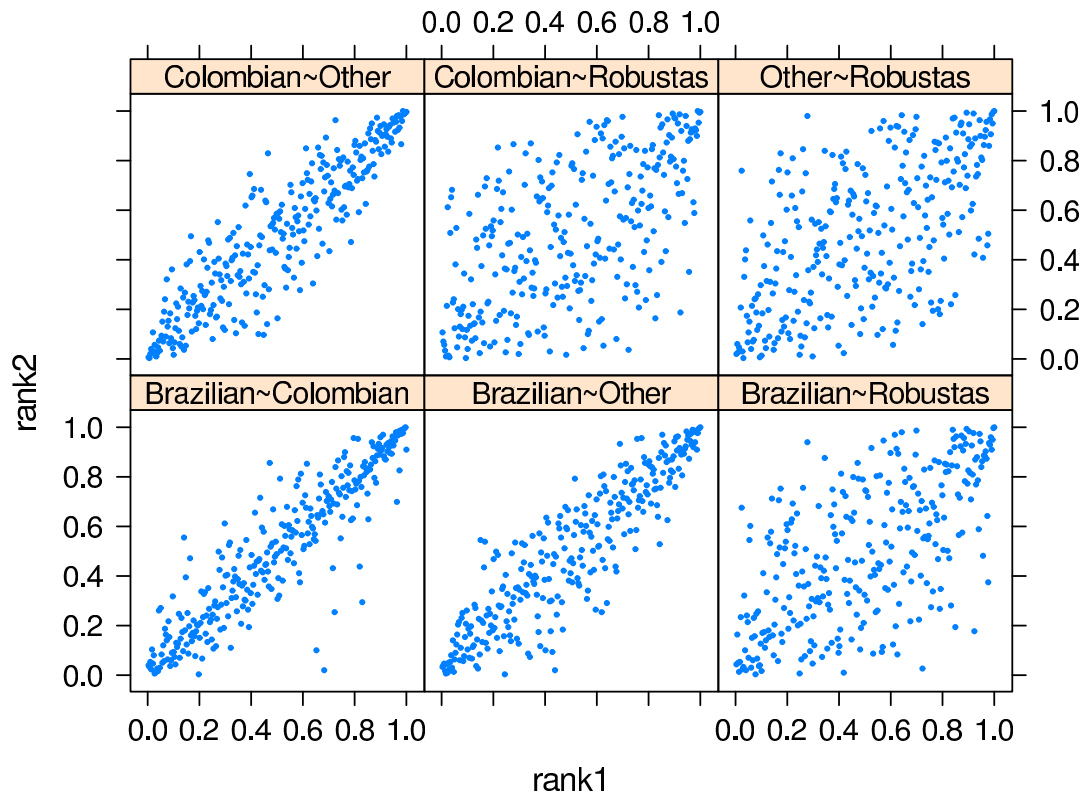

Figure 5: Scatterplots of the copula data (ranks). Data have been plotted as rank2~rank1, with rank1 on the horizontal axis and rank2 on the vertical axis respectively.

6   Copula stability

Before concluding this work, we need to test for time–varying dependence of the copula i.e. whether there is stability in the selected copula family. Empirical evidence suggests that the degree of co–movement between random variables may change when the market environment changes. A number of alternative measures regarding the co–movement of random processes have been proposed in the literature (Manner and Reznikova, 2012; Reznikova, 2012). In this work we utilized Kendall's τ, which
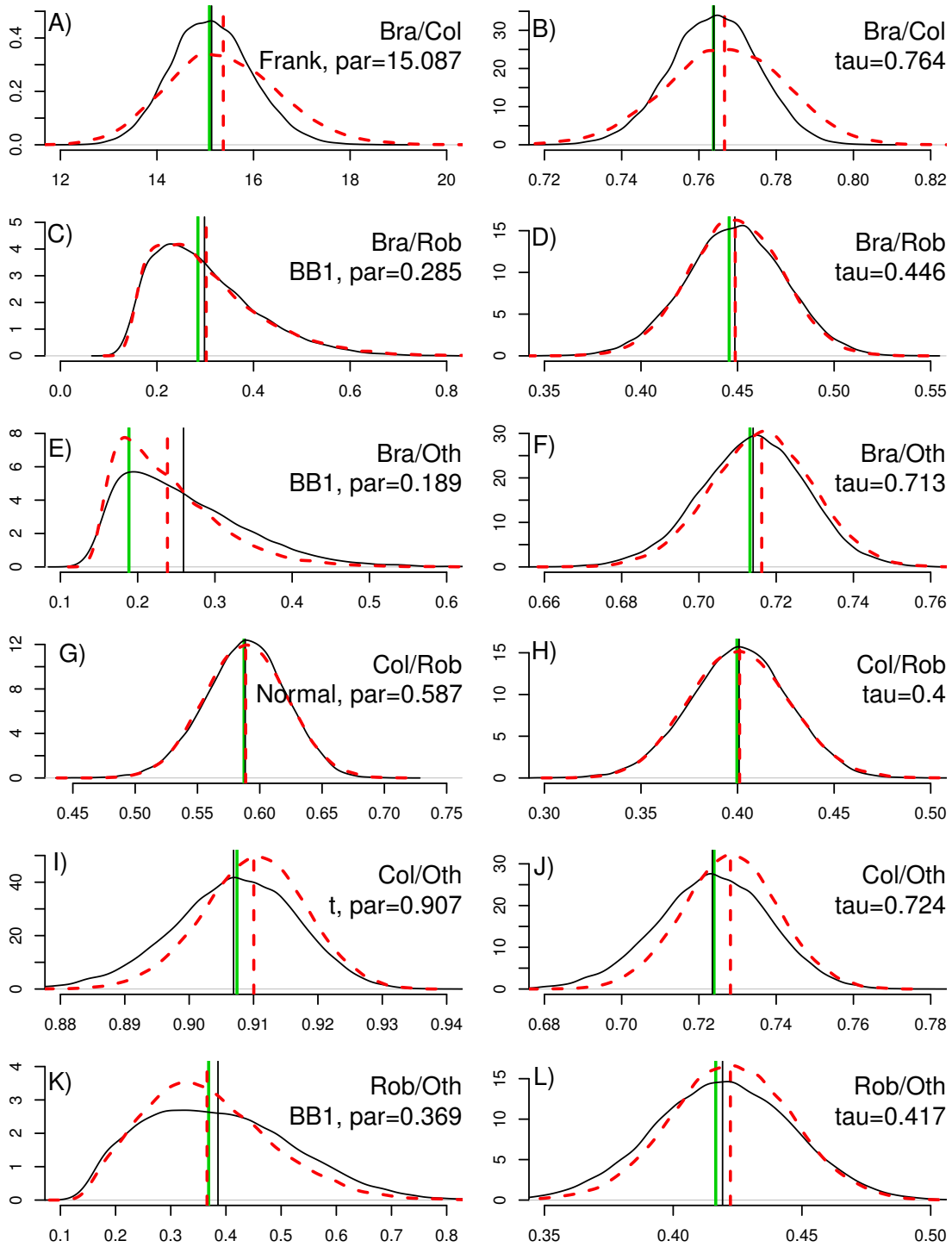
Figure 6: Density plots of copula parameter(s) and Kendall's tau from parametric and non-parametric 20,000 bootstrap repetitions for the six pairs of coffee qualities. Notation of graphs: continuous black curve = parametric bootstrap, dashed read curve = non-parametric bootstrap, green vertical line = estimated parameter of the original sample, black vertical line = mean of parametric bootstrap, dashed vertical red line = mean of non-parametric bootstrap.
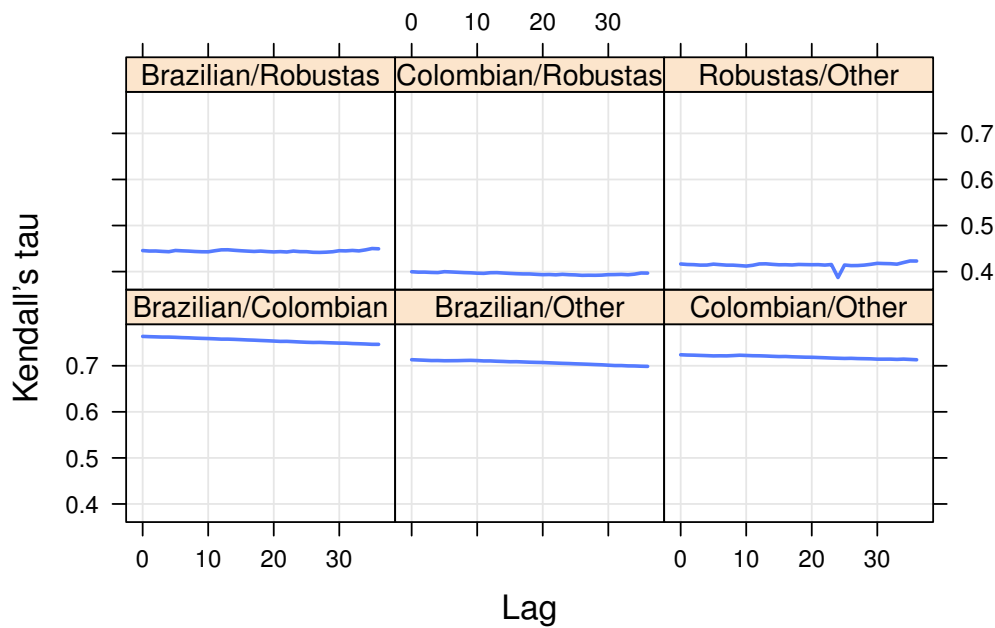
Figure 7: Plot of Kendall's τ estimator with 36 lags

provides information on the co–movement at the center and at the tails of the joint distribution function. Hence, we test for time-varying dependence using Kendall's τ estimation over a rolling window (Zhang and Guéganc, 2008) of the price time series over 36 periods (month by month).

Figure 7 presents graphically how the the estimated values of Kendall's tau, for each one of the six different pairs of coffee qualities, fluctuate with time. As we can observe, the estimates of Kendall's tau are quite stable and are not characterized by significant fluctuations. Hence, it would be safe to conclude that the selected copula families for the six coffee pairs are not characterized by time–varying dependence.

7 Conclusions

There is emerging consensus that the international agri-food system is becoming more vulnerable to extreme events of price volatility. Asymmetries in the transmission of price volatility has always been in the center of attention in agricultural and food economics, since this might be an indicator of economic inefficiency.

In the coffee market, the abandonment of coffee quotas regulated by the International Coffee Agreement in 1989 led to a worldwide fall in producer prices for coffee. In the mid–nineties coffee prices recovered for some time but in the late 1990s coffee prices decreased drastically to their lowest real levels of the century (Kilian et al., 2006). 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 varieties/species, namely Arabica and Robusta.

In this context, the objective of this work was to assess the nature of price dependence between four different coffee qualities: Colombian Arabicas milds, Brazilian and other natural Arabicas, Other mild Arabicas and Robustas. The first three are of the Arabica variety and considered to be of higher quality. Robusta is mainly produced by African countries and it is considered to be of relatively lower quality in comparison with the Arabica. The statistical methodology we used was that of copulas. Copulas are a useful tool in order to investigate bivariate interdependencies of economic data. Our results reveal evidence of asymmetric price dependence between the pairs Brazilian–Robusta, Brazilian–Others and Others–Robusta, since price booms and price crashes are transmitted with different probabilites between these three pairs of coffee qualities. On the other hand, for the pairs Brazilian–Colombian, Colombian–Robusta and Colombian–Others there is no evidence of asymmetric price dependence.

To explain the estimated price dependence structure and their implications on coffee producers we relied on information about coffee production worldwide as well

as the fairtrade scheme of coffee certification. Seventy–seven per cent of fairtrade coffee production comes from Latin American countries, where higher quality Arabica coffee is produced. According to the results of this work, the probability that fairtrade coffee producers will see a price crash in the Robusta variety being transmitted to the Arabica variety is either zero (Col/Rob) or much lower than the probability of the transmission of a price boom (Bra/Rob, Rob/Oth).

The present study relies on bivariate copulas. Remarkable progress towards developing and implementing higher order copulas has been made by recent works (Acar et al., 2012; Czado et al., 2012). Hence, future research may consider multivariate copulas in order to assess price dependence in the coffee market.

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