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Price co-movement and the hedger's value-at-risk in the futures markets for coffee

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Abstract

This work investigates the strength and the pattern of co-movement between the futures price of the Arabica coffee (traded in New York) and the futures price of the Robusta coffee (traded in London) and obtains forecasts for the Value-at-Risk (VaR) for a commercial trader. The empirical analysis relies of the statistical tool of copulas and on daily observations from 2006 to 2016. According to the empirical results, co-movement is symmetric with respect to sign but is asymmetric with respect to size. The Value-at-Risk ranges from -7 percent to -3 percent, depending on the level of confidence employed.

Keywords: Coffee Futures, Copulas, Value-at-Risk
JEL Classification: Q13, C10

1. Introduction

Coffee is, value-wise, among the most important internationally traded commodities. The cash market for physical coffee is deep and liquid, physical coffee can be standardized, and its price exhibits considerable volatility both with respect to size as well as with respect to the suddenness of shocks (The Coffee Guide, 2016; International Coffee Organization - ICO, 2014). The characteristics of the underlying physical commodity market and the need for risk management by exporters and roasters of coffee beans have long provided the economic basis for the establishment of highly successful futures markets for coffee.

There are two principal futures markets centres serving the global coffee industry: the Intercontinental Exchange (ICE) in New York and the International Futures and Options Exchange (LIFFE) in London. The ICE contract (market symbol KC) is the world benchmark for Arabica coffee; the size of a single contract in the ICE is 17 metric tons and the quotation is in cents per libre. The LIFFE contract (market symbol RC) is the world benchmark for Robusta coffee; the size of a single contract in the LIFFE is 10 metric tons and the quotation is in $US per ton.

Against this background, the objective of the present work is to investigate price interdependence (co-movement) and price risk in the two principal exchanges for coffee (the ICE and the LIFFE). The strength and the pattern of price linkages between coffee futures concern academics, commercial traders, and non commercial traders[1]. The ICE and the LIFFE are geographically separated markets. At the same time, the coffee futures traded in each of the two exchanges represent quality differentiated (substitutes to each other) physical commodities. In the short-run, therefore, there is room for commodity arbitrage (both inter-

[1] Commercial traders are those using the futures markets primarily to hedge their business activities. Non commercial traders (speculators) are not involved directly in the production or consumption of the underlying physical commodity; they risk their own capital (provide liquidity) in the futures markets with the hope of making profit from price changes (CFTC, 2016). Among the non commercial traders are individual investors, hedge funds, and large financial institutions.

market and inter-commodity one). Arbitrage in the physical and/or in the commodity quality space ensures that price shocks in one market will evoke responses to the other market. In the long-run, the arbitrage opportunities will be exhausted and the price difference (spread) between any two markets will not exceed the sum of transaction costs and the quality premium (Law of One Price - LOP) (e.g. Fousekis et al., 2016; Reboredo, 2011; Serra et al., 2006; Asche et al., 1999).

Agents involved in the trade of physical coffee closely monitor the price spread between the ICE and the LIFFE futures since it is a key determinant of their business profitability. To protect themselves from unfavourable future price movements they may resort to the so called spread hedging, a limited-risk strategy involving a commercial trader taking opposite positions at the ICE and at the LIFFE. For example, a roaster may go long in New York (i.e. buy Arabica futures) and simultaneously go short in London (i.e. sell Robusta futures). With this strategy, the commercial trader on the one hand "locks-in" the spread and on the other reduces the risk; because Arabica and Robusta are substitutes, their futures prices are expected to co-move and, thus, potential gains from one position will be offset by potential losses from the opposite position. It is obvious that the success of the spread hedging strategy depends critically on the degree of co-movement between the two futures prices (strong positive co-movement implies lower risk). Non commercial traders, in contrast, go long (short) in coffee futures when they anticipate prices to increase (decrease). Strong co-movement results into higher returns (losses) in the case their bet on price changes succeeds (fails).

The empirical analysis of price co-movement and price risk here relies on copulas, a statistical tool that has been proved to be very suitable for modelling multivariate distributions of random processes. There have been, however, very few studies that employed copulas in portfolio risk management, in general, and in the assessment of the Value-at-Risk (VaR), in particular (Fantazzini, 2008; Bastanin, 2009; Lu et al. , 2014, and Ghorbel and Trabelsi, 2014). Their results appear to suggest that capturing adequately the salient features of the underlying multivariate distributions such as asymmetries and fat tails is of paramount importance for delivering accurate VaR forecasts.

The above mentioned works have viewed portfolio risk from the vantage point of a non commercial trader. In commodity markets, however, hedgers (commercial traders) constitute a large part of all traders. According to the CTFC (2016) the traders of coffee futures classified as Producers, Merchants, and Processors accounted for 35.5 percent of the total open interest in the ICE during 2015[2]. Commercial and non commercial traders have different objectives and face different market risk. In what follows, Section 2 presents the analytical framework and Section 3 the empirical models and the empirical results. Section 4 offers conclusions and suggestions for future research.

2. Analytical framework

2.1 Assessing co-movement with copulas

Consider a 2-dimensional random vector $Y = (Y_1, Y_2)'$ with joint distribution function

[2] The LIFFE does not publish reports on the commitment of trades. One, however, expects that the share of commercial traders in the total open interest for Robusta coffee will be comparable to that for the Arabica.

$F(y_1, y_2)$ and with continuous marginal distribution functions $F_i(y_i) \quad (i=1,2)$. Sklar's (1959) Theorem suggests that F can be factored into its marginal and a joining function termed as copula. Technically,

$$F(y) = C(F_1(y_1), F(y_2)) \qquad (1),$$

where C is the copula function mapping the univariate marginal distribution functions to their joint distribution function. The probability integral transforms, $U_i = F_i(y_i)$, follow the uniform distribution on [0, 1] irrespective of the F_i. Therefore, the copula may be interpreted as a joint distribution function with uniform marginals on [0,1] relating the quantiles of the univariate distributions rather than the original stochastic processes. As such, the copula function is scale invariant (i.e. unaffected by strictly increasing transformations of Y_1 and Y_2) (e.g. Reboredo, 2011; Patton, 2013). Further advantages of copulas are that they yield information both about the strength as well as about the structure of linkages and they offer a natural framework for testing asymmetric co-movement. The converse of Sklar's Theorem holds in the sense that given two marginal distributions $F_i(y_i) \quad (i=1,2)$ and a copula C, the function F defined by (1) is a valid bivariate distribution.

There are two types of co-movement measures, namely, the global and the local. The former provide information about the intensity of co-movement between random processes over their entire joint support. The most commonly employed measure of global co-movement is Kendall's tau (τ). It is derived from the copula function as

$$\tau(Y_1, Y_2) = 4\int_0^1\int_0^1 C(u_1, u_2)dC(u_1, u_2) - 1 \qquad (2)$$

and it stands for the difference between the probability of concordance and the probability of discordance..

The intensity of co-movement at subsets of the join support (i.e. locally) is measured by the quantile coefficients (e.g. Patton, 2013). The first, λ_{LL} or Lower-Left is defined as

$$\lambda_{LL}(q) = \mathrm{P}(U_2 \le q / U_1 \le q) = \frac{C(q,q)}{q}, \quad 0 < q \le 0.5 \qquad (3)$$

and the second, λ_{UR} or Upper-Right is defined as

$$\lambda_{UR}(q) = \mathrm{P}(U_2 > 1-q / U_1 > 1-q) = \frac{2q-1+C(1-q,1-q)}{q}, \quad 0 < q < 0.5 \qquad (4).$$

λ_{LL} (λ_{UR}) provides the probability that the random process Y_2 receives a value lower (higher) than its q (1-q) quantile given that the random process Y_1 receives a value lower (higher) than its q (1-q) quantile, as well (Patton, 2013; Vandenberghe et al., 2010). By varying q one may trace out how the strength of the relationship behaves at the different parts of the support. Note that for radially symmetric copulas it is the case that $\lambda_{LL}(q) = \lambda_{UR}(q)$ for all q<0.5.

Among the different patterns of asymmetric price co-movement of particular importance are the asymmetry with respect to sign and the asymmetry with respect to size (e.g. Frey and Manera, 2007; Mayer and von Cramon Taubadel, 2004). Under the former, price shocks of the same absolute magnitude and of opposite sign are transmitted from one market to another with different intensity; under the latter, price shocks of the same sign and of different magnitude are transmitted from one market to another with different intensity. A formal test of asymmetry with respect to sign for a given level of q< 0.5 has been proposed by Patton (2013). The null hypothesis is $H_0 : \lambda_{LL}(q) = \lambda_{UR}(q)$, rejection of which offers empirical evidence that the probability of co-movement for price shocks with magnitude above the median is different from that of price shocks with magnitude below the median[3]. Recently, Fousekis and Grigoriadis (2016) developed a formal test of asymmetry with respect to size utilizing the monotonicity property of the quantile coefficients (Caillault and Guegan, 2005). For the coefficient λ_{LL} and for three quantile levels q_1, q_2, and q_3 such that $0 \le q_1 < q_2 < q_3 < 0.5$ and $q_1 = q_3 - q_2$, the null hypothesis is $H_0 : \lambda_{LL}(q_1) = \lambda_{LL}(q_3) - \lambda_{LL}(q_2)$ or $\lambda_{LL}(q_1) - (\lambda_{LL}(q_3) - \lambda_{LL}(q_2)) = 0$ rejection of which implies that the probability of co-movement between larger price shocks is different from the probability of co-movement between smaller price shocks. For the λ_{UR} coefficient, one arrives at exactly the same null hypothesis considering quantile levels q_1, q_2, and q_3 such that $0.5 < 1 - q_3 < 1 - q_2 < 1 - q_1 \le 1$ with $q_1 = q_3 - q_2$ and utilizing again the monotonicity property.

The presence of asymmetric co-movement with respect to sign or to size for given quantiles of the joint distribution of price shocks can be empirically verified by employing a Wald-type test, the sample statistic of which is

$$(R\hat{\lambda})'(R\hat{V}_B R')^{-1}(R\hat{\lambda}) \quad \sim \quad \chi_1^2 \qquad (5),$$

where R is a restrictions' matrix, $\hat{\lambda}$ a vector of quantile coefficients estimates, and $\hat{V}_B$ is the bootstrap estimate of their variance-covariance matrix (Patton, 2013).

2.2 Forecasting the VaR with copulas

The Value-at-Risk (VaR) is the measure that provides a simple answer to the question: " what is the maximum loss which may be incurred by a portfolio over a specific time horizon with probability level α? " (Lu et al., 2014; Bastanin, 2009). For the bivariate case, consider a commercial trader who goes long in one commodity and simultaneously goes short in the other. Let also that she(he) buys k_1 contracts from the first commodity and sells k_2 contracts from the second. The value of her (his) portfolio at time t is then

$$V_t = k_1 Q_1 p_{1t} - k_2 Q_2 p_{2t} \qquad (6),$$

where p_{it} are the contract prices and Q_i are the contract sizes $(i = 1, 2)$. The Profit and Loss (P&L) function, that means, the percentage change in the portfolio's value from period t-1 to t is

[3] If the median is zero, rejection of the null implies different probabilities of co-movement between negative and positive shocks at the quantiles *q* and 1-*q*, respectively.

$$P\&L_t = \sum_{i=1}^{2} w_{it} p_{it-1}(\exp(r_{it})-1) \qquad (7),$$

where r_{it} are the price log returns (i.e. $r_{it} = \ln(p_{it} / p_{it-1})$) and w_{it} $(i=1,2)$ are the weights of the commodities in the portfolio. Note that the weight of the first commodity is positive while the weight of the second is negative, and that $\sum_{i=1}^{2} w_{it} = 1.$

The VaR satisfies

$$P(L_t > VaR_t(\alpha)) = 1-\alpha \Rightarrow P(L_t \le VaR_t(\alpha)) = \alpha \qquad (8),$$

where L stands for loss (in percentage terms). Denoting as $G_{P\&L}$ the distribution function of the portfolio's log returns one gets

$$VaR_t(\alpha) = G^{-1}_{P\&L_t}(\alpha) \qquad (9).$$

From the last follows that the VaR is nothing else than the α quantile of the probability density function of the P&L.

An extension of the VaR measure is the Tail VaR (or Conditional VaR-CVaR) giving the expected loss in the case of a lower tail event. It is obtained as

$$CVaR_t(\alpha) = E(L_t \mid L_t \le VaR_t(\alpha)) \qquad (10).$$

For any α it is the case that $CVaR_t(\alpha) < VaR_t(\alpha).$

The one-dimensional distribution function $G_{P\&L}$ depends on the two-dimensional (d-dimensional, in the general case) joint distribution function F of the log-returns via equation (9). Here, the converse of Sklar's (1959) Theorem comes into play by allowing a researcher to obtain the joint distribution function of the price log-returns using their marginals and an appropriate copula function.

3. The data, the empirical models, and the empirical results

3.1. The data and the univariate analysis

The data for the empirical analysis are daily prices of nearby KC and RC contracts; they have been obtained from Quantl (2016) and refer to the period 1/1/2006 to 30/6/2016 (a total of 2399 observations). Figure 1 presents the natural logarithms of the two prices and of their spread. The contract prices exhibit certain long periods of downturns and upturns. The long sequences of falling or rising prices indicate that trading coffee futures is pretty risky (e.g. Burkhardt et al., 2013). Long periods of downturns and upturns are evident in the spread between the two contract prices as well.

In line with all earlier studies on price co-movement and/or on risk measuring with copulas (e.g. Panagiotou and Stavrakoudis, 2015; Lu et al., 2014; Ghorbel and Trabelsi, 2014; Patton, 2013; Reboredo, 2012; Bastanin, 2009) the present work focusses on the linkages between the price log returns, denoted as dKC and dRC for the Arabica and the Robusta contracts, respectively.

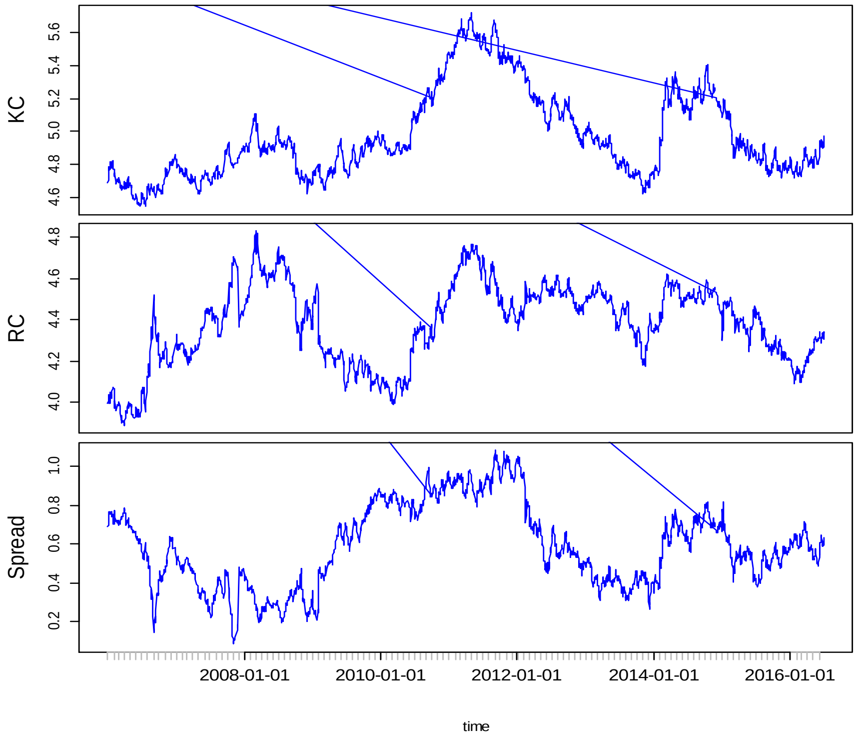

Fig. 1. - *Natural logarithms of the prices and of their spread*

The asymptotic properties of copula estimators have been established under the assumption of i.i.d. observations (e.g. Patton, 2013; Remillard, 2010; Fermanian and Scaillet, 2003). Time series data such as price log returns, however, may exhibit serial correlation and ARCH effects. To account for this potential problem and following all relevant past empirical works (e.g. Emmanouilides and Fousekis, 2015; Lu et al., 2014; Reboredo 2012; Serra and Gil, 2012) the individual series of price log returns (price shocks) have been filtered using ARMA-GARCH marginal models with Skewed Generalized Error Distribution-SGED. Filho et al. (2012) note that skewed versions of GARCH models ensure that any asymmetry found in a multivariate co-movement structure is genuine and not a consequence of marginal misspecification. Table A.1 (Appendix) presents the estimation results. The filtered data have been then converted into copula data using probability integral transforms and a scaling factor equal to $T/T+1$ (e.g. Fousekis and Grigoriadis, 2016; Panagiotou and Stavrakoudis, 2015), where T is the sample size.

3.2. The bivariate analysis and the VaR

An important issue in the empirical investigation of price linkages with copulas is that of the invariance of co-movement (e.g. Emmanoulidies and Fousekis, 2015; Lu et al., 2014; Patton, 2013; Reboredo, 2012). When the strength of interdependence changes with time, the copula estimate obtained under the assumption of time-invariant co-movement over the entire sample may be misleading. This issue has been investigated here using Patton's (2013) approach that relies on an autoregressive-type model the dependent variable of which is the contemporaneous product of the copula data from the two series. The copula is constant when the autoregression coefficients (up to a certain lag) are jointly equal to zero. The test has been performed for 1, 6, and 12 lags. Table 1 presents the results. The null hypothesis of time-invariant co-movement is not rejected at any reasonable level of significance.

Tab. 1. *- Patton's test results on time-invariant co-movement**

AR(l)		
1	6	12
0.391	0.478	0.604

* l is the number of lags; the p-values come from a Wald-type test on the joint significance of the coefficients $\gamma_i \ (i = 1,...,l)$ of the autoregressive model $v_{1t}v_{2t} = \gamma_0 + \sum_{i=1}^{l} \gamma_l v_{1t-l} v_{2t-l} + \varepsilon_{it}$, where v_{it} denotes copula data.

Bivariate stochastic processes may exhibit quite different salient features (e.g. heavy tails and/or asymmetric co-movement). Here, to determine the most suitable copula family we have selected formally among 17 families using the Akaike and the Schwartz Information Criteria which have been shown to perform reasonably well in this context (e.g. Dißmann et al., 2013). Table A.2 (Appendix) presents the results. Both criteria suggest that the radially symmetric Student-t is the family fitting the copula data better relative to the rest.

Tab. 2. *Estimates of Price Co-movement **

Coefficient	Estimate
$\lambda_{LL}(0.01)$ and $\lambda_{UR}(0.01)$	0.267 (0.015)
$\lambda_{LL}(0.025)$ and $\lambda_{UR}(0.025)$	0.307 (0.013)
$\lambda_{LL}(0.05)$ and $\lambda_{UR}(0.05)$	0.349 (0.011)
$\lambda_{LL}(0.10)$ and $\lambda_{UR}(0.10)$	0.410 (0.01)
$\lambda_{LL}(0.20)$ and $\lambda_{UR}(0.20)$	0.496 (0.009)
$\lambda_{LL}(0.30)$ and $\lambda_{UR}(0.30)$	0.572 (0.008)
$\lambda_{LL}(0.40)$ and $\lambda_{UR}(0.40)$	0.639 (0.007)
Kendall's *tau*	0.399 (0.012)

* Standard errors in parentheses. They have been obtained using block bootstrap (Patton, 2013) with 1000 replications.

Table 2 presents the estimate of global co-movement as well as estimates of local co-movement at a number of quantiles. Given that the Student-t copula is radially symmetric, local co-movement at symmetric positions along the positive diagonal (e.g. at the 0.05 and the 0.95 quantiles) is the same. Table 3 presents the test results for symmetry with respect to size. The null hypothesis is rejected very strongly for all combinations considered. The sign of the estimates is positive suggesting that larger (in absolute value) shocks in one of the prices are transmitted to the other price with higher intensity compared smaller shocks. This pattern complies with theoretical and empirical results of the price transmission literature pointing to the existence of inactivity bands around the median (i.e. for small price shocks) and to thresholds that price shocks in one market have to surpass in order to trigger responses in another market (e.g. Frey and Manera, 2007; Mayer and Cramon von Taubadel, 2004).

Tab. 3. - *Test results for symmetry with respect to size **

Null Hypothesis	Estimate
$\lambda_{LL}(0.025)-(\lambda_{LL}(0.05)-\lambda_{LL}(0.025))=0$ and $\lambda_{UR}(0.025)-(\lambda_{UR}(0.05)-\lambda_{UR}(0.025))=0$	0.264 (0.00)
$\lambda_{LL}(0.05)-(\lambda_{LL}(0.10)-\lambda_{LL}(0.05))=0$ and $\lambda_{UR}(0.05)-(\lambda_{UR}(0.10)-\lambda_{UR}(0.05))=0$	0.289 (0.00)
$\lambda_{LL}(0.10)-(\lambda_{LL}(0.20)-\lambda_{LL}(0.10))=0$ and $\lambda_{UR}(0.10)-(\lambda_{UR}(0.20)-\lambda_{UR}(0.10))=0$	0.321 (0.00)
$\lambda_{LL}(0.20)-(\lambda_{LL}(0.40)-\lambda_{LL}(0.20))=0$ and $\lambda_{UR}(0.20)-(\lambda_{UR}(0.40)-\lambda_{UR}(0.20))=0$	0.361 (0.00)

* *p*-values from the Wald test in parentheses.

For the VaR analysis, this work considers a roaster who buys 1 contract of Arabica in New York and sells simultaneously 1 contract of Robusta in London[4]. Prior to using the ARMA-GARCH models along with the copula estimates in performing the out-of-sample VaR forecasts, the adequacy of the estimated models has been evaluated using in-sample backtesting based on Christoffersen's (1998) unconditional coverage test. Table A.3 (Appendix) presents the expected exceedances, the actual exceedances, and the p-values for the test at different levels of α. In all cases, the null hypothesis (i.e., there is no difference between expected and actual exceedances) is supported by the data.

Table 4 presents the h=1 and the h=22 (approximately one month) step-ahead VaR and CVaR forecasts from the hedger's P&L function[5]. The differences in the results between the two

[4] The results will not change if one considers a roaster using the same combination of contracts who goes short in New York and long in London. Note that all earlier empirical studies consider portfolios where assets are equally weighted. For portfolios with commodity futures, however, equal weights may arise from pure coincidence only. This for two reasons: (a) commodities have different futures prices in different exchanges and (b) contract sizes may be different (as it is the case with the KC and the RC ones). The portfolio assumed here is not necessarily optimal since the latter will depend on a commercial's desired blend of coffee beans (a firm's secret recipe). Nevertheless, it appears to be much more realistic than one involving equal weights. Moreover, the use of 1 contract from each variety suggests that, in terms of physical quantities, one unit of Arabica is combined with 0.59 (=10/17) units of Robusta. This is very close to the composition of the global production of coffee (61 percent Arabica and 39 percent Robusta). In our portfolio, the average weight (based on prices and contract sizes) for the Arabica is 1.51 and for the Robusta is -0.51.

[5] The *h*-day ahead VaR forecast at confidence level $(1-\alpha)\%$ can be calculated from the following steps (Lu *et al*., 2014):

1. The ARMA-GARCH models are estimated for each of the price log return series using *T* observations.
2. The *h*-step ahead means and standard deviations are forecasted (denoted as

forecast periods are very small. The VaR (%) ranges from -0.066 for $\alpha = 0.01$ to -0.03 for $\alpha = 0.1$; the respective values for the CVaR (%) are -0.079 and -0.045. Table 5 presents the same forecasts in $1000 (absolute values). The VaR ranges from 1.19 to 2.54 and the CVaR from 1.77 to 3.31 thousand dollars.

Tab. 4. - *VaR and CVaR forecasts from a hedger's P&L function**

Value of α				
(%)	0.01	0.025	0.05	0.10
VaR and CVaR forecasts (*h*=1)				
VaR	-0.065	-0.052	-0.041	-0.030
CVaR	-0.078	-0.065	-0.056	-0.046
VaR and CVaR forecasts (*h*=22)				
VaR	-0.066	-0.053	-0.042	-0.031
CVaR	-0.079	-0.066	-0.056	-0.045

* results based 100000 simulated values; the portfolio value for a speculator is $V_t = k_1 Q_1 p_{1t} + k_2 Q_2 p_{2t}$

Tab. 5. *VaR and CVaR forecasts for a hedger's portfolio (absolute values)**

Value of α				
(in $1000)	0.01	0.025	0.05	0.10
VaR and CVaR forecasts (*h*=1)				
VaR	2.499	1.885	1.576	1.153
CVaR	2.978	2.499	2.150	1.730
VaR and CVaR forecasts (*h*=22)				
VaR	2.537	1.998	1.614	1.191
CVaR	3.307	2.536	2.150	1.769

* calculated from the VaR(%) and CVaR (%) and the average value of the historical portfolio

For completeness and comparison, the Value at Risk has been analysed here for a non commercial trader as well. Tables A.4 and A.5 (Appendix) present the results. The VaR and the CVaR, in percentage terms, for the speculator are lower (about 2/3 of those for the commercial trader); the VaR and the CVaR in $1000, however, are higher (about 1.4 times of those for the hedger). This is reasonable since the speculator's portfolio value, for the same combination of contracts, is almost 2 times the hedger's portfolio value (on average, the former has been 73.37 and the latter 38.44 thousand dollars).

$\hat{r}^{\,i}_{T+h}$ and $\hat{\sigma}^{\,i}_{T+h}$, respectively, for $i = KC, RC$).

3. The selected copula is estimated and its parameters are used to simulate N Monte Carlo scenarios (obtaining, thus, N Monte Carlo data pairs $(\hat{u}^{KC}_j, \hat{u}^{RC}_j)$ for $j = 1, \dots, N$).

4. The Monte Carlo data along with the forecasted means and standard deviations are used to form new standardized residuals (price log returns). The latter are substituted in (7) to yield N P&L forecasts, $(P \,\&\, L)^j_{T+h}$.

5. Finally, the forecasts are sorted in an increasing order and the $\alpha\%$ VaR is obtained as the α empirical quantile of the $(P \,\&\, L)^j_{T+h}$ $(j = 1, 2, \dots, \mathrm{N})$.

4. Conclusions

The strength and the pattern of co-movement between commodity futures prices is of interest for academics and traders for two reasons: First, it offers an indication of the degree of market integration (efficiency); second, it is a key determinant of the risk involved in physical and in futures exchanges. This work investigates price co-movement and price risk in coffee futures traded at the ICE and the LIFFE. The investigation relies on the statistical tool of copulas and on daily price observations from 2006 to 2016.

The empirical results suggest:

1. The degree of global co-movement is relatively high; 70 percent of the observations are concordant and only 30 percent are discordant.
2. There is sizable and statistically significant co-movement at the tails implying that extreme shocks have a strictly positive probability of transmission from one market to the other.
3. The pattern of co-movement is best captured by the radially symmetric Student-t copula. Therefore, positive and negative price shocks of the same absolute magnitude are transmitted with the same intensity in all parts of the joint support.
4. There is asymmetric co-movement with respect to size in the sense that larger in absolute value price shocks are transmitted with higher intensity compared to smaller ones. It appears that, because of the transactions cost involved in futures trading, large price shocks are required to make position changes worthwhile.
5. For a hedger, the value at risk at the very extremes (equal to or less than 0.01) is close to 7% of the total portfolio value; for a speculator it is less than 5%. The investment of the noncommercial, however, is substantially larger than that of the commercial. As a result, the speculator faces a greater amount of risk when measured in terms of dollars to be lost in the case of an extreme market downswing.

The VaR analysis here relies on the assumption that the trade involves a single contract from each coffee variety. It is not necessarily, however, representative of the situation on the ground. The reason is that commercial traders are likely to buy and sell combinations of futures contracts having their desired (undisclosed to the public) blends in mind. The above points to one avenue for potential future research. One could employ alternative scenarios (combinations) and compare the amount of risk involved in each one of them. It is likely that as a hedger considers more unbalanced combinations (that is, combinations with large number of contracts from one variety and small number of contracts from the other) she (he) will end up with a higher amount of risk since such combinations tend to weaken the beneficial effect of the positive co-movement between the futures prices in the two exchanges.

Another potential avenue could involve a 4-dimentional analysis with two futures and two spot coffee prices. For a hedger, spot prices are certainly relevant in his decision to fulfil a futures contract (i.e. to deliver/accept delivery) or to offset it and to buy/sell the physical commodity locally. It appears that there are two difficulties with regard to the latter avenue. The first has to do with the data; the ICO started publishing daily spot prices of different coffee varieties very recently (since mid-2014). The second has to do with the dimensions of the model; it is well known that the flexible parametric Archimedean copulas require severe parameter restrictions when applied to three or more stochastic processes (Nelsen, 2006). A solution to this problem may come through the of use non parametric copula estimation techniques. Recently, Racine (2015) proposed a non parametric approach which appears to be suitable for multidimensional processes. In any case, further research on the topic copulas and VaR assessment is certainly warranted.

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Appendix

Tab. A.1: - *Estimates of the ARMA-GARGH Models**

Coefficient	*dKC*	*dRC*
mu	0.0003 (0.402)	-0.00009 (0.011)
ar1	-0.273 (0)	-0.788 (0)
ar2	-0.251 (0)	-1.139 (0)
ar3	0.047 (0.022)	-0.481 (0)
ar4	-	-0.0067 (0)
ma1	0.234 (0)	0.807 (0)
ma2	0.246 (0)	1.139 (0)
ma3	-	0.499 (0)
ω	0.00001 (0)	0.00006 (0.224)
$\alpha 1$	0.0244 (0)	0.109 (0.034)
$\beta 1$	0.958 (0)	0.739 (0)
Skew	1.019 (0)	1.009 (0)
Shape	1.273 (0)	0.987 (0)

* *p*-values in parenthesis; the AIC has been used to select the lag length.

Tab. A.2. - *The results from the copula selection process*

Copula Family	AIC	SBIC	Copula Family	AIC	SBIC
Gaussian	-985.76	-979.97	BB8	-907.042	-895.48
Student-*t*	-1032.42	-1020.86	Survival Clayton	-721.73	-715.92
Clayton	-831.92	-826.14	Survival Gumbel	-978.72	-972.94

Gumbel	-906.28	-900.50	Survival Joe	-786.98	-781.20
Frank	-935.45	-929.67	Survival BB1	-1022.97	-1011.41
Joe	-665.15	-659.37	Survival BB6	-976.54	-964.98
BB1	-1019.43	-1007.87	Survival BB7	-994.98	-983.41
BB6	-904.01	-892.45	Survival BB6	-943.70	-932.137
BB7	-996.75	-985.18			

Tab. A.3. - *Results of the unconditional coverage test*

Value of α				
	0.01	0.025	0.05	0.10
Expected exceedances	23	59	119	239
Actual Exceedances	18	50	116	240
p-value	0.459	0.407	0.713	0.976

Tab. A.4. *VaR and CVaR forecasts from a speculator's P&L function**

Value of α				
(%)	0.01	0.025	0.05	0.10
VaR and CVaR forecasts (*h*=1)				
VaR	-0.045	-0.036	-0.029	-0.020
CVaR	-0.056	-0.047	-0.039	-0.032
VaR and CVaR forecasts (*h*=22)				
VaR	-0.047	-0.037	-0.030	-0.021
CVaR	-0.057	-0.048	-0.040	-0.033

* results based 100000 simulated values

Tab. A.5. *VaR and CVaR forecasts for a speculator's portfolio (absolute values)**

Value of α				
(in $1000)	0.01	0.025	0.05	0.10
VaR and CVaR forecasts (*h*=1)				
VaR	3.375	2.641	2.127	1.468
CVaR	4.109	3.448	2.861	2.348
VaR and CVaR forecasts (*h*=22)				
VaR	3.495	2.752	2.231	1.562
CVaR	4.239	3.569	2.975	2.454

* calculated from the VaR (5) and CVaR (%) and the average value of the historical portfolio