The Relationship between Oil and Brazilian Agricultural Commodities Prices

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THE RELATIONSHIP BETWEEN OIL AND BRAZILIAN AGRICULTURAL COMMODITIES PRICES

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ABSTRACT

Many empirical studies have been conducted on the influence of international crude oil price movements on several markets, particularly on commodity markets which are crucial to the world economy. This paper aims to examine the conditional correlation between the returns of oil prices and certain agricultural commodities price returns, using appropriate multivariate GARCH models. The selection of such agricultural commodities takes into account their relevant weight in the Brazilian foreign trade. The results suggest that these models can be used for forecasting the behavior of the above-mentioned markets. All data have been obtained from weekly time series of the Brent type crude oil prices, in US$ per Barrel, and selected commodities FOB prices. The time period spanned by the analysis ranges from February 2004 to February 2012.

Keywords: Conditional Correlation; Volatility Models; Crude Oil Prices; Commodity Markets.

JEL Classifications: C32, L71, O13, Q17, Q40.

INTRODUCTION

Food provision plays an important role in the economic development of many countries, especially in the Brazilian economy due to the substantial volume exported abroad and the high domestic demand. With the recent financial crisis and downturn in the largest economies of the world, food has become more expensive and its production has decreased significantly.

Nowadays, many decisions are taken based on the price of agricultural commodities. Producers must have some kind of estimate on future price behavior to decide the amount of capital they should invest or even borrow from others. Safety-net arrangements shall be made by the government in some countries so that compensation for loss of revenue suffered by producers can be automatically paid should a fall in prices or any other crisis render the sector even more vulnerable. Investors often make use of the agricultural commodities future markets to reduce the risk in their investment portfolios. In this context, many researches have been conducted to study the major influences which led to the increase in volatility in food products during the last years. Recent experience suggests that the extremely volatile international oil market have direct and indirect effects on many commodity markets, especially those related to the main arable crops. Musser et al. (2006) argues that, due to massive investments from farmers on oil based products and energy, the intensive agricultural production in developed countries rely heavily on fossil energy. Chen et al. (2010) investigated the relationship between crude oil price and global grain prices using recent time series data and found that the change in each grain price is significantly affected by the changes in crude oil prices and other grain prices. The empirical results of Udoh (2012) provide clear evidence that there is a strong casual relationship between oil price distortions and food price instability in Nigeria. With a differentiated approach, Gohin and Chantret (2010) used a general equilibrium model to investigate the long-run association between world prices of some food and energy products and found a positive relationship due to the cost-push effect.

On the whole it can be inferred that there has been a significant increase not only in the prices of the grains, but also in their volatility on a global scale excepting cases such as protectionist practices by the government in some countries, crop and in-between harvest periods, grain storage, among others. It is also taken for granted that these prices are, to a certain degree, associated with the international oil market.

In the context of the above mentioned situation and taking into account the important role the agricultural commodities play in the Brazilian foreign trade, this paper aims to investigate the dynamic association between the returns of crude oil prices and certain grain prices returns such as soybeans, sugar and coffee. In order to do so, appropriate multivariate GARCH models were used on weekly time series of the Brent type crude oil prices and selected commodities prices.

This paper is organized as follows. The next section presents the data used in this work and the methodological approach was treated in section 3. The results obtained were discussed in the section 4 while the conclusions and final remarks were treated in the section 5. At the end of this paper the references used was listed.

DATA – SAMPLE USED

Crude oil prices data, particularly the Brent oil type prices, were collected from the U.S. Energy Information Administration (EIA). As for the soybeans, we made use of the ESALQ/BM&FBOVESPA Soya Price Index, which consists of an arithmetic average of the soya prices marketed in the Paranaguá Port, Brazil. The values correspond to the closing prices, in Brazilian Real (R$), of the soybean sack (60 kg) in the last trading day of the week. These prices are converted to the commercial dollar price at 16:30 p.m. (Brasilia time), when the national soya market closes The reference for sugar prices is the CEPEA/ESALQ - São Paulo Crystal Sugar Price Index, which is commonly used to estimate the Total Recoverable Sugar (ATR) price per ton of sugarcane. All transactions are reported in Brazilian Real (R$) per sack of granulated sugar (50 kg) and the market closing price is converted to the commercial dollar price. Finally, concerning the coffee prices, the Arabica coffee price was considered as reference. The price index chosen to represent the price values is also the CEPEA/ESALQ, which corresponds to the coffee "type 6" - one of the best quality coffees. Just like the soybeans, all transactions are reported in Brazilian Real (R$) per bag of coffee beans (60 kg) and the market closing price is converted to the commercial dollar price.

After having obtained all the above mentioned data, the price returns time series were generated from the original price time series by making use of a differentiation mechanism, whose general formula is:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where P_t represents the original price time series and R_t is the generated price returns time series.

Figures 1 to 4 illustrate the data for each commodity weekly price time series used and their corresponding returns. It came as no surprise that crude oil prices time series is non-stationary. Figure 1 suggests that the oil price returns time series have a constant mean, with periodic fluctuations around this mean. These fluctuations seem to share the same amplitude scaling, except for the period between late 2008 and early 2009, where it is remarkable the increased volatility in oil price returns due to the global financial crisis.

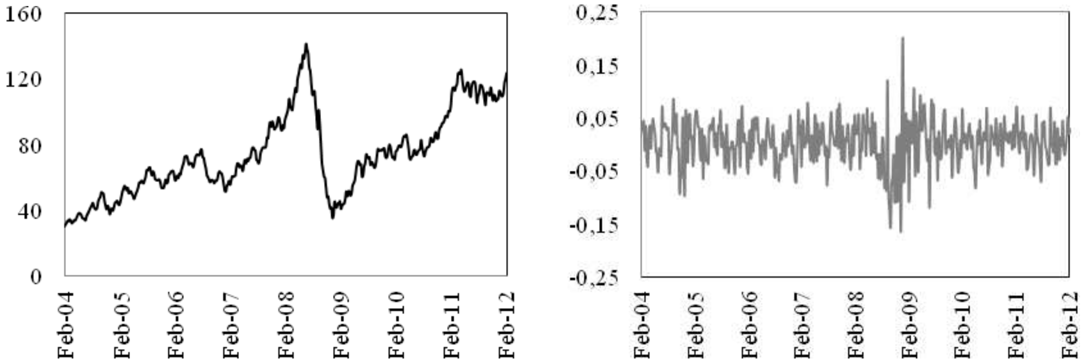

Figure 1. Crude Brent oil type prices and returns

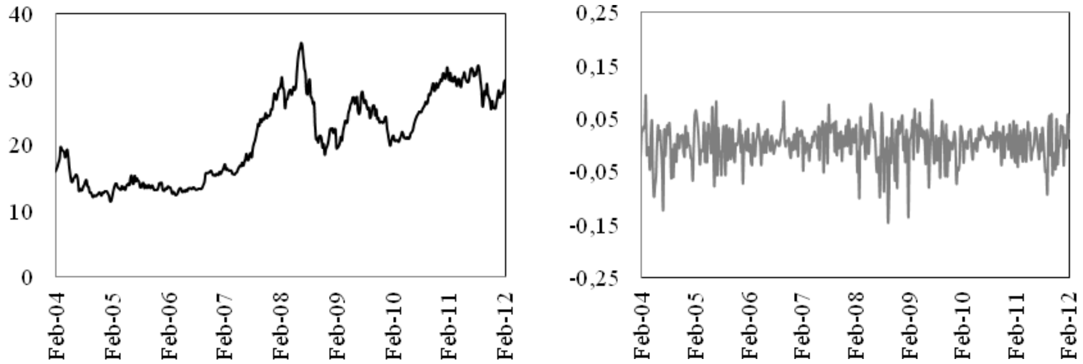

Figure 2. Soybean prices and returns

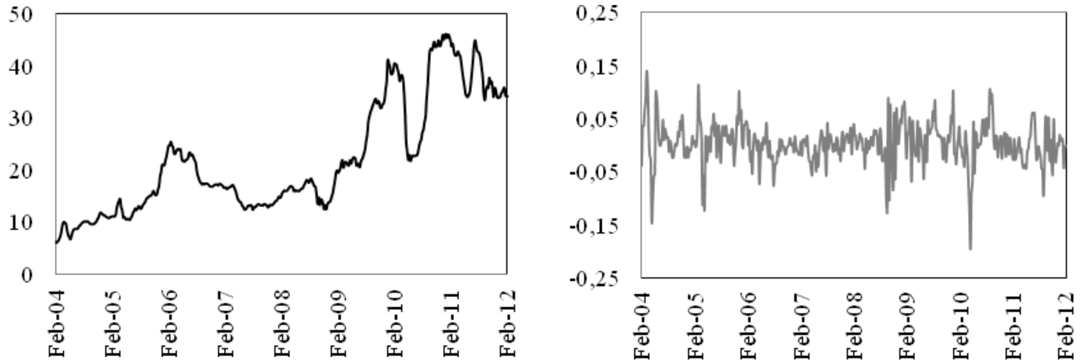

Figure 3. Crystal Sugar prices and returns

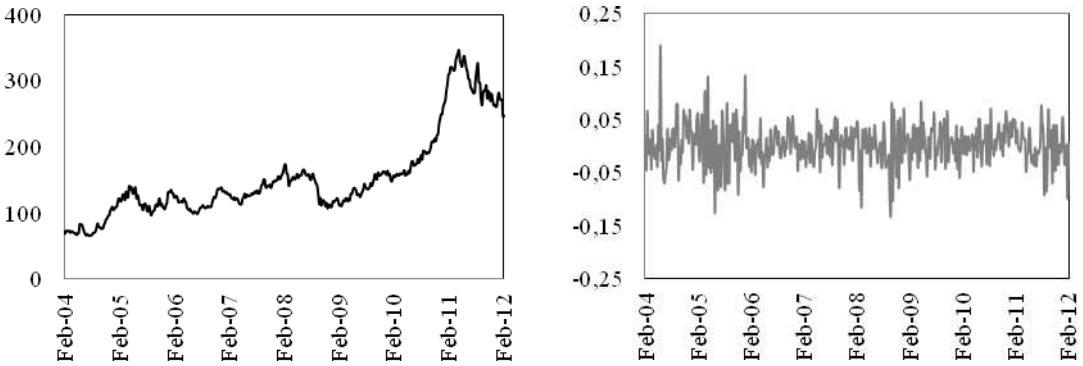

Figure 4. Arabica Coffee prices and returns

The graphical analysis of the soybean price quotations, as shown in Figure 2, also indicates a positive trend in the prices of the grain over the years. By contrast, there are no notable trends readily apparent in the price returns of the grain. This pattern suggests that the price returns series studied by far are really stationary. The volatility effects are somewhat strengthened between late 2008 and early 2009 as a result of the world economic crisis, although to a lesser extent than the crude oil price scenario. The situation does not change when analyzing the data for the Crystal Sugar price quotations. Figure 3 shows another typical example of a decidedly upward trend in the commodity prices. However, there is also another remarkable thing in the price chart: a radical change in price levels from the beginning of 2009, where the commodity has experienced an upturn in its values since the last financial crisis. This significant shift in price levels may have something to do with a new pricing policy after the crisis and we suggest that this change should be further investigated. As for the sugar price returns, again there is no apparent reason for the time series to be non-stationary, just like in the other cases. However, Figure 3 shows some remarkable negative returns of greater magnitude in specific periods of the year. This could be linked to the seasonal component of the time series due to the harvest and intercrop periods of the sugarcane. Also, it is important to point out that the sugar bean production in Brazil depends largely on the price of ethanol, as producers can easily change their final product according to the market conditions, since there is no consistent national policy to regulate the sugar industry. As well as in the other case scenarios, the graphic chart for the weekly Arabica Coffee quotations exhibits a clear positive trend over the years, as it can be seen in Figure 4. Also, just like the sugar prices, there is a noticeable change in trading price levels, this time, however, from the beginning of February 2010. Coffee price returns present a similar behavior to that of other studied commodities price returns, with no well-defined tendencies. Some greater magnitude price fluctuations occur in the years 2004 and 2005 and the reason behind these spikes is another point that could be further investigated.

Many conclusions can be drawn from the graphical analysis. However, eyeballing the new generated data is not a substitute for formally testing for the presence of non-stationary behavior. In this work the Augmented Dickey-Fuller (ADF) test was used to verify the stationarity hypothesis for the time series involved. Besides stationarity, another important thing to check is whether the time series data is assumed to follow a normal distribution or not. Unlike stationarity, the presence of normality in a time series is not a prerequisite for modeling, but one must test for normality in order to choose which model best fit the data, as there are specific stochastic processes for each case. There are many ways to determine whether a dataset is well-modeled by a normal distribution or not. A more comprehensive test, as long as the data contains a decent amount of observations, is the Jarque-Bera test. This test checks if the asymptotic results for skewness and kurtosis match a normal distribution.

Table 1 gives an overview of the main descriptive statistics for each price returns time series, also showing the results obtained from the Jarque-Bera and Augmented Dickey-Fuller tests, to verify the presence of normality and stationarity, respectively, in each dataset used here. All price returns time series have a null mean. Also, in all four cases, the presented values for the mean and median are very similar, which could indicate the presence of symmetry in the data. However, the values obtained for the skewness and kurtosis suggest that the normality assumption of the data set might not be valid. That is subsequently confirmed by the Jarque-Bera test results, which demonstrate that the normality assumption of the data could not be accepted, as the p-value obtained in each JB test can be approximated by zero in all four cases. Therefore, one must take this fact into consideration when modeling. For instance, choosing to model the error terms of the data by another distribution rather than the normal, that is the Student's t distribution, would definitely contribute to better estimation results.

Table 1. Statistical Summary

	Price Returns			
Statistic	Brent	Soya	Sugar	Coffee
Mean	0.0034	0.0014	0.0041	0.0030
Median	0.0061	0.0058	0.0043	0.0033
Maximum	0.2002	0.0926	0.1411	0.1903
Minimum	-0.1646	-0.1441	-0.1954	-0.1294
Standard Deviation	0.0424	0.0345	0.0389	0.0393
Skewness	-0.3290	-0.7820	-0.4858	-0.0135
Kurtosis	4.6781	4.5860	6.0225	4.6969
Observations	420	420	420	420
Jarque-Bera	56.8587	86.8199	176.3846	50.4008
p-value	0.0000	0.0000	0.0000	0.0000
τ statistic (ADF)	-5.7222	-18.5557	-8.7864	-6.5740
Critical Value (τ) for α = 1%	-3.9805	-3.9801	-3.9802	-3.9805

METHODOLOGY

The main purpose of this work is to estimate the degree to which our variables are related, that is, the conditional correlation between the international oil market and the selected agricultural commodity markets. The most common measure of correlation is the Pearson product moment correlation and this was used to infer the level of association between oil price returns and the agricultural commodities price returns. When computed in a sample, the "Pearson's r" formula is:

$$r = \frac{COV(X,Y)}{S_x S_y} \tag{2}$$

where $COV(X,Y)$ is the covariance between two random variables and S_x and S_y represents the standard deviations of X and Y, respectively. After having generated the conditional correlation time series for each bivariate case, as the formula is computed for each weekly observation during the time period, it is important to make sure that the values obtained are statistically significant. In order to do so, a significance two tailed t test is applied on each correlation result according to the following formula:

$$t_{(n-2\,d.f.)} = \frac{r}{\sqrt{1-r^2}}\sqrt{n-2} \tag{3}$$

where n represents the number of previous observations. The statistical test has a Student´s t distribution with n - 2 degree of freedom. The values of the covariance and standard errors, used to compute the conditional correlation, are estimation results generated through a specific model and that is why particular attention should be paid to the selection of the best model for each bivariate case - oil price returns and some of the agricultural commodity price returns. In this paper a wide range of conditional volatility models which take into account the heteroskedasticity of the data are proposed and tested. These models are briefly discussed in the following paragraphs.

One way of measuring volatility is through the autoregressive conditional heteroskedasticity (ARCH) process, first proposed by Engle (1982). The key idea of an ARCH model is that the conditional variance of the error term at time *t* depends on the squared error term at time *t-1*. Later on, Bollerslev (1986) came up with a variation of the Engle ARCH processes by introducing past lags of the conditional variance, suggesting a generalization of ARCH model designated by GARCH model. After that, a whole new set of variations of the original GARCH models were proposed by many authors. A large body of this literature has been devoted to univariate models. However, what is at stake here are the co-movements of price returns. Therefore, this paper focuses on an extension of the GARCH-M models for the multivariate case. These models were first proposed by Bollerslev et al. (1988) when looking for efficient Capital Asset Pricing Models (CAPM). There are various parametric formulations for multivariate GARCH models. The first representation was the VECH-GARCH model of Bollerslev, Engle, and Wooldridge (1988), a straightforward generalization of the univariate GARCH-M model. The idea was to use vectors instead of scalars and a variance-covariance matrix rather than the variance. In order to evaluate the conditional volatility of financial assets, the authors designated y_t as the vector of (real) excess returns of all assets in the market and u_t and H_t, respectively, as the conditional mean vector and conditional covariance matrix of these returns given information available at time *t-1*. Furthermore, they let ω_{t-1} be the vector of value weights at the end of the previous period so that the excess return on the market can be represented as $y_{M_t} = y_t' \omega_{t-1}$. Thus, the vector of covariances with the market is simply $H_t \omega_{t-1}$ and the CAPM requires $u_t = \delta H_t \, \omega_{t-1}$ where δ is a scalar constant of proportionality measuring the relative risk aversion. Without extending our scope beyond the article, the equations estimated by the models are as following:

$$y_t = b + \delta H_t \, \omega_{t-1} + \epsilon_t \tag{4}$$

$$vech(H_t) = C + \sum_{i=1}^{q} A_i vech(\epsilon_{t-i}\epsilon_{t-i}') + \sum_{j=1}^{p} B_j vech(H_{t-j}) \tag{5}$$

$$\epsilon_t | \psi_{t-1} \sim N(0, H_t) \tag{6}$$

where the excess returns y_t is an *N x 1* vector and H_t is a *N x N* conditional variance-covariance matrix. b is an *N x 1* vector of constants and ϵ_t is an *N x 1* vector of innovations or random disturbances. For the second part, $vech(\,)$ denotes the operator that stacks the lower triangular portion of a symmetric *N x N* matrix into an $N(N+1)/2$ vector of the corresponding unique elements, and A_i and B_j are parameter matrices of compatible dimension $N(N+1)/2 \;\; x$ $N(N+1)/2$ while C is an $N(N+1)/2$ vector of constant terms. Finally, for the last equation, ψ_{t-1} stands for the set of available information at previous time *t* -1. For the particular case of a bivariate GARCH(1,1) model and disregarding specific components pertaining to the CAPM case, such as the ω_{t-1} vector, the previous equations (5) and (6) can be written as:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} + \begin{bmatrix} H_{11,t} & H_{12,t} \\ H_{21,t} & H_{22,t} \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \tag{8}$$

$$\begin{bmatrix} H_{11,t} \\ H_{21,t} \\ H_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} \\ c_{21} \\ c_{22} \end{bmatrix} + \begin{bmatrix} a_{11,1} & a_{12,1} & a_{13,1} \\ a_{21,1} & a_{22,1} & a_{23,1} \\ a_{31,1} & a_{32,1} & a_{33,1} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t-1}^2 \\ \epsilon_{1,t-1}\epsilon_{2,t-1} \\ \epsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11,1} & b_{12,1} & b_{13,1} \\ b_{21,1} & b_{22,1} & b_{23,1} \\ b_{31,1} & b_{32,1} & b_{33,1} \end{bmatrix} \begin{bmatrix} H_{11,t-1} \\ H_{21,t-1} \\ H_{22,t-1} \end{bmatrix}. \tag{9}$$

A potential problem that arises from this parametric formulation is that it does not guarantee that the resulting conditional covariance matrices are positive definite. There are no restrictive conditions for H_t to be positive definite for all t, just sufficient conditions. Another disadvantage of this unrestricted vech representation is that it involves a huge number of parameters to be estimated, $(p+q)(N(N+1)/2)^2 + (N(N+1)/2)$ to be more specific, which is computationally demanding. In light of these problems, Bollerslev et al. (1988) proposed a more parsimonious version of the unrestricted model to obtain conditions for H_t to be positive definite for all t. They assumed the matrices A_i and B_j are both diagonal, so that each element in H_t depends exclusively on its own lagged values and the product of the corresponding shocks. In this parametrization, designated by Diagonal VECH, the estimation is less difficult than in the unrestricted VECH model since each equation can be estimated separately. In addition, the number of estimated parameters is smaller compared to the complete VECH representation.

For the particular case of a bivariate GARCH(1,1) model, the Diagonal VECH parametric formulation can be expressed as follows:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} + \begin{bmatrix} H_{11,t} & H_{12,t} \\ H_{21,t} & H_{22,t} \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \tag{10}$$

$$\begin{bmatrix} H_{11,t} \\ H_{21,t} \\ H_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} \\ c_{21} \\ c_{22} \end{bmatrix} + \begin{bmatrix} a_{11,1} & 0 & 0 \\ 0 & a_{22,1} & 0 \\ 0 & 0 & a_{33,1} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t-1}^2 \\ \epsilon_{1,t-1}\epsilon_{2,t-1} \\ \epsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11,1} & 0 & 0 \\ 0 & b_{22,1} & 0 \\ 0 & 0 & b_{33,1} \end{bmatrix} \begin{bmatrix} H_{11,t-1} \\ H_{21,t-1} \\ H_{22,t-1} \end{bmatrix}. \tag{11}$$

Even with all the convenience of the Diagonal VECH compared to its previous, unrestricted formulation, a model that contains $(p+q+1)N(N+1)/2$ parameters seems too restrictive. Moreover, the positive definite restriction of the covariance matrices cannot be taken for granted in a hundred percent of cases.

A formulation that can be viewed as a restricted version of the VECH model is a specific parameterization of the multivariate GARCH model defined in Engle and Kroner (1995). This formulation is called BEKK, an acronym that stands for Baba, Engle, Kraft and Kroner and has the following form:

$$H_t = C'C + \sum_{i=1}^{q} A_i' \epsilon_{t-i} \epsilon_{t-i}' A_i + \sum_{j=1}^{p} B_j' H_{t-j} B_j, \tag{12}$$

where now C, A_i and B_j are N x N matrices, being C lower triangular. In this model the conditional covariance matrices are positive definite by construction, which is an attractive property. Once again, with particular regard to a bivariate GARCH(1,1) model, previous equation (12) can be written as:

$$\begin{bmatrix} H_{11,t} & H_{12,t} \\ H_{21,t} & H_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & 0 \\ c_{12} & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t-1}^2 & \epsilon_{1,t-1}\epsilon_{2,t-1} \\ \epsilon_{2,t-1}\epsilon_{1,t-1} & \epsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix} \begin{bmatrix} H_{11,t-1} & H_{12,t-1} \\ H_{21,t-1} & H_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}. \tag{13}$$

Finally, it is also possible to assume the matrices A_i and B_j to be both diagonal, coming to a further simplified model called Diagonal BEKK, which has less parameters to be estimated than the unrestricted version.

All multivariate heteroskedastic volatility models discussed so far consist of stochastic processes to represent the variance component of the price returns time series. However, it is also necessary to model the conditional mean of these time series. A good starting point is to simply assume a constant mean throughout time. This is the most elementary representation of the conditional mean and has yielded satisfactory results in many cases, as the main issue in almost every multivariate approach for financial time series is their volatility, which is linked to the variance component. The general formula for a constant mean model would be:

$$r_{x,t} = c_x + \epsilon_{x,t} \tag{14}$$

where $r_{x,t}$ is the vector of returns, with x being the number of series included in the multivariate analysis, c_x is the vector of independent terms and $\epsilon_{x,t}$ is the vector random disturbances. For the particular bivariate case, the matrix representation is:

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}. \tag{15}$$

Another easy alternative to represent the conditional mean of time series in a multivariate analysis is to make use of an autoregressive model. An AR(p) model is defined as:

$$r_{x,t} = c_x + \sum_{i=1}^{p} \beta_{x,i}\, r_{x,t-i} + \epsilon_{x,t} \tag{16}$$

where the new term $\beta_{x,i}$ represents the matrix of coefficients related to the i lags of included returns ($r_{x,t-i}$) in the analysis. Considering an AR(1) bivariate case, the matrix representation would be:

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \beta_{1,1} \\ \beta_{2,1} \end{bmatrix} \begin{bmatrix} r_{1,t-1} \\ r_{2,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}. \tag{17}$$

A different approach is to use a Vector Autoregression (VAR) model that has the advantage of treating all variables involved as a priori endogenous. In other words, current values of a set of variables are partly explained by past values of the variables involved. A VAR(1) model was used and can be written as:

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \beta_{1,1} & \gamma_{1,1} \\ \beta_{2,1} & \gamma_{2,1} \end{bmatrix} \begin{bmatrix} r_{1,t-1} \\ r_{2,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}. \tag{18}$$

where $\beta_{x,t}$ and $\gamma_{x,t}$ are unknown parameters to be determined. For each case a VAR(1) model with no intercepts was also estimated as this sometimes leads to substantial gains in the final results. The representation is the same as the previous one above, excepted for the c_x vector that no longer exists.

At this point, it is not difficult to notice the multitude of possible combinations to model the joint time series involved, even for the bivariate case. In addition, it is also possible to relax or restrict certain conditions in almost every model, which creates even more possibilities for modeling. In front of this, some filtering has to be done so that we select the best fit models to estimate the conditional correlation between the price returns time series. This is going to be done in two stages. The first step is to look at the statistical significance of the estimated parameters. For each independent term and regressor obtained, a Z test is run to determine whether the parameter is statistically different from zero or not. This maneuver dramatically reduces the number of potential models to be used in each analysis. The subsequent step is to refine our selection by making use of some information criteria. The rule of thumb is to opt for the model which generates the lowest values of the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn Criterion (HQ).

In the next section the results obtained using this methodology are presented.

RESULTS AND DISCUSSIONS

For each bivariate case, a total of 228 models have been tested, each one combining different stochastic processes. To represent the conditional mean component of the joint time series analysis, the following processes have been chosen: a constant mean model, just intercepts; a bivariate autoregressive process of order 1 - an AR(1) model; a vector autoregression of order 1 - VAR(1) - with intercepts; and a vector autoregression of order 1 - VAR(1) - with no intercepts. These models are straightforward solutions to represent the conditional mean of the joint time series, ensuring easy configuration and estimation of parameters.

Table 2. Estimation results of the selected bivariate models for each case

Parameter	Brent-Soya *Constant Mean* *VECH-GARCH(1,1)*	Brent-Sugar *VAR(1) with intercepts* *VECH-ARCH(1)*	Brent-Coffee *AR(1) with intercepts* *BEKK-GARCH(1,1)*
Mean Representation			
C_1	0.0057 (0.0018)	0.0039 (0.0008)	0.0045 (0.0018)
C_2	0.0034 (0.0016)	0.0032 (0.0004)	0.0047 (0.0017)
$\beta_{1,1}$	-	0.1774 (0.0306)	0.2154 (0.0468)
$\gamma_{1,1}$	-	0.0669 (0.0335)	-
$\beta_{2,1}$	-	-0.0900 (0.0118)	-0.0802 (0.0454)
$\gamma_{2,1}$	-	0.4252 (0.0199)	-
Variance Representation			
c_{11}	0.0001 (0.0000)	0.0019 (0.0006)	0.0001 (0.0000)
c_{12}	0.0000 (0.0000)	0.0010 (0.0003)	0.0000 (0.0000)
c_{22}	0.0000 (0.0000)	0.0005 (0.0002)	0.0000 (0.0000)
$a_{11,1}$	0.0905 (0.0319)	2.4701 (0.6841)	0.2539 (0.0535)
$a_{12,1}$	0.0786 (0.0325)	0.6973 (0.3834)	-
$a_{22,1}$	0.0756 (0.0240)	4.4443 (1.2256)	0.1594 -0.0301
$b_{11,1}$	0.8694 (0.0470)	-	0.9481 (0.0205)
$b_{12,1}$	0.7734 (0.0740)	-	-
$b_{22,1}$	0.8990 (0.0289)	-	0.9865 (0.0044)
Information Criteria			
AIC	-7.6512	-7.0911	-7.3806
BIC	-7.5454	-6.9754	-7.2746
HQ	-7.6094	-7.0453	-7.3387

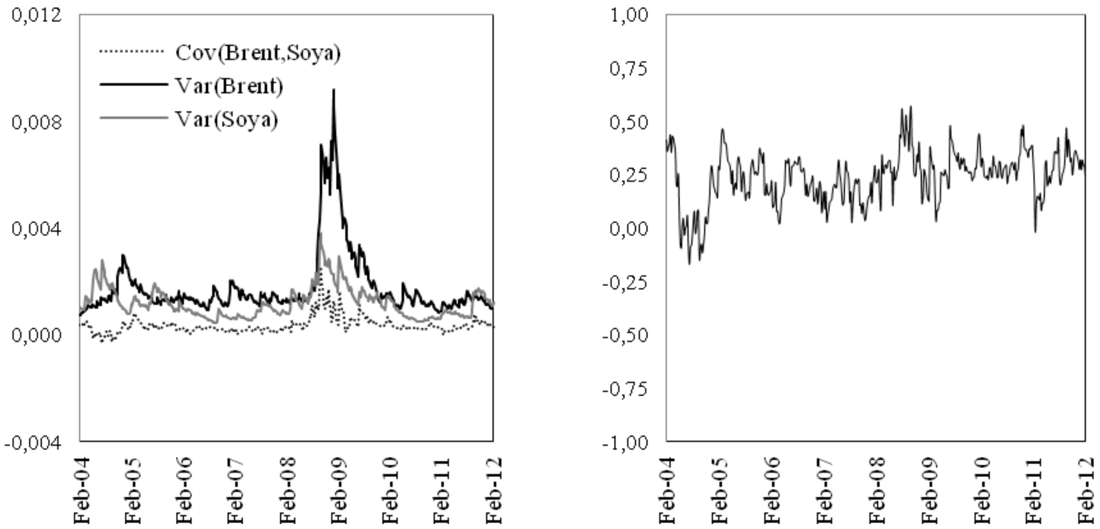

Figure 5. Brent-Soya - Variances and Conditional Correlation time series

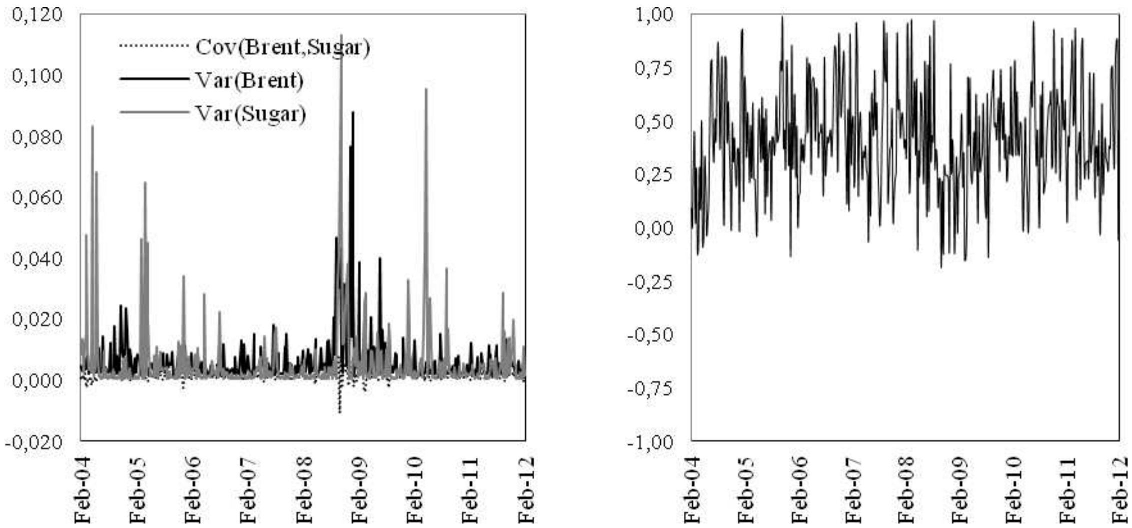

Figure 6. Brent-Sugar - Variances and Conditional Correlation time series

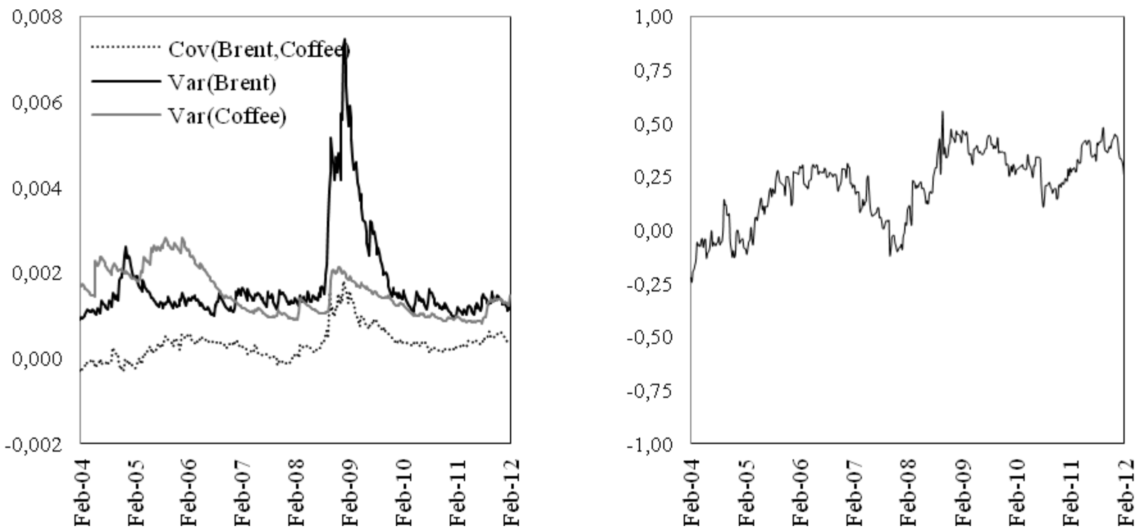

Figure 7. Brent-Coffee - Variances and Conditional Correlation time series

As for the modelling of variance and covariance components, the range of possibilities is enormous, as noted in the previous session. However, the most simple stochastic process of the GARCH family - the GARCH(1,1) process - has proven to be adequate and responsive in order to model the volatility of the involved time series in a multivariate scenario, as empirical evidence suggests. In this paper, besides the GARCH(1,1) process, we also estimate the variance component through a bivariate ARCH(1) formulation, a simpler approach which also yields satisfactory results. With regards to the parametric representations, we test both the unrestricted and diagonal versions of the VECH and BEKK formulations, mentioned in the previous session. There is also a wide range of variations in these representations, as it is possible to relax or impose certain conditions for the parameter matrices. In this work, the following conditions have been considered: concerning the independent terms (intercepts), we assume the matrices to be diagonal, rank 1, full rank or indefinite; regarding the parameters related to the past values of the squared error terms and variance, we assume the matrices to be diagonal, full rank or indefinite.

The parameters results obtained by the estimation of the models selected in each bivariate case are shown in Table 2. The values in brackets are standard deviations of each estimated parameter. As mentioned before, the selection of these models takes into account the greatest number of the statistically significant parameters and the smallest values of the most commonly used information criteria: AIC, BIC and HQ. The results for these criteria are also listed in the lower part of Table 2. From a total of 228 estimated models for the joint analysis of the Brent oil price returns and the soyabeans price returns, the best combination was the Constant Mean Model with a VECH-GARCH(1,1) specification for the variance, assuming the following conditions for the coefficient matrices: to represent the intercepts (independent terms), a rank 1 matrix; for parameters related to the past values of the squared error terms (ε^2) and to the past values of the variance (σ^2), indefinite matrices. For the association between the Brent oil price returns and the Crystal Sugar price returns, the combination which produced the best results was the following: a Vector Autoregression of order 1 - VAR(1) -, with intercepts, for the conditional mean component and a VECH-ARCH(1) specification for the variance, assuming the following conditions for the coefficient matrices: a rank 1 matrix to represent the intercepts and a full rank matrix containing the parameters related to the past values of the squared error terms. Finally, for the last case, in order to study the relationship between the returns of the crude Brent oil prices and the domestic Arabica Coffee prices, a bivariate AR(1) process was chosen to represent the conditional mean with a BEKK-GARCH(1,1) specification for the variance, assuming the following conditions for the coefficient matrices: a rank 1 matrix to represent the intercepts and diagonal matrices for the parameters related to the past values of the squared error terms and the variances.

After the selection of the best-fit model, the values for the variances and the covariance between the oil price returns and the soya price returns were estimated. The results are shown in Figure 5. There is a sharp contrast between the variance levels for each commodity price returns. As expected, these values are considerably higher for the Brent oil, due to its greater volatility in the international market. Such difference was even more pronounced during the period between late 2008 and early 2009, where it is remarkable the increased volatility in both commodities price returns due to the global financial crisis. As for the covariance analysis, the graphic shows that its values remained almost unchanged for the greater part of the analysis period, with the exception of the late 2008-early 2009 time frame, where they raised substantially. The generated conditional correlation time series for the Brent-soya case is also displayed in the second chart of Figure 5. The majority of the observations correspond to positive values. However, these values are often modest for the greater part of the analysis period, although still significant. This is an indication that there is indeed an undeniable association between the involved markets, however this relationship is not very strong. In other words, it is possible to make use of the crude oil prices history to explain partly the domestic Brazilian soya market. Finally, it is also important to notice that the correlation values were considerably higher during the period between late 2008 and early 2009. As later shown by the descriptive analysis of the Brent-Soya conditional correlation time series in Table 3, the mean of these association values is approximately 0.24 for the entire period of the analysis, whereas the values obtained during the late 2008-early 2009 time frame may be even higher than 0.48, twice the normal average. Finally, as for the statistical significance of the association between the Brent oil price returns and the soyabean price returns, the conditional correlation seems to be statistically significant in 300 of the 420 observations taken into account, at the 5% significance level. Hence, it can be stated, with a small margin of error, that the association between the involved markets is real, even though somewhat weak.

The results obtained for the relationship between the Brent oil price returns and the Crystal Sugar price returns differ substantially from the previous case. Firstly, unlike the soybean price returns, the price returns for the Crystal Sugar are extremely volatile during certain periods of the year, with its variance even surpassing the crude oil variance in some cases, as shown in Figure 6. A more detailed analysis of the chart reveals that all major volatility peaks in the Brazilian crystal sugar market occur between the months of April and May. This is a strong indication of seasonality and should be further investigated in future works. As for the covariance analysis, the situation is also different from the previous bivariate case: although the covariance values also remain almost unchanged for the greater part of the analysis period, a sharp decrease occurs in the months between late 2008 and early 2009. This may suggest that the involved markets distanced themselves during the global financial crisis, although this is not very clear. In order to be more accurate, it is important to look at the second chart of Figure 6, which shows an extremely volatile conditional correlation time series. This was already to be expected since the variance values obtained for the price returns of the two involved commodities are considerably high. However, despite the many ups and downs in the generated time series, it is remarkable that the association between the involved markets is way superior than the one for the Brent-soya case. As shown later in the descriptive statistics for the generated conditional correlation time series in Table 3, the mean value for the association is 0.4123, which is considerably high, taking into account that the crystal sugar market studied is of national scale. Finally, after applying the two tailed *t* test of significance for the conditional correlation values, the results indicated a total of 353 statistically significant observations. Thus, the association between the international Brent oil type market and the Brazilian Crystal Sugar market is no doubt strong and real.

Finally, for the association between the Brent oil price returns and the Arabica Coffee price returns, the variance values for both involved commodities seem to be quite similar during most part of the studied period, being slightly higher for the crude oil price returns, as it can be seen in Figure 7. The exceptions are: the first years of the analysis (2004-2006), where the coffee market was highly volatile, with its variance surpassing the crude oil variance, and during the global financial crisis, where the variance levels for both commodities price returns peaked, but the effect was of greater magnitude in the international oil market this time. With regard to the covariance, similar to the Brent-soya case and unlike the Brent-Sugar, its values increased considerably in the months between late 2008 and early 2009, suggesting that the involved markets became more closely associated during the crisis. In order to prove this hypothesis, we take a look at the results for the conditional correlation values, shown as time series plots in the second chart of Figure 7. Besides ups and downs, there is a clear positive trend in the conditional correlation values during the studied period. These raises have become even more pronounced after the crisis, with many observations already surpassing the 0.40 mark. This is a substantial change if we compare these values from those obtained in the beginning of the analysis, where most of them were virtually nil or even negative. Perhaps after the crisis there may have been some substantial changes either in the domestic coffee market or in the international oil market that may have contributed to a greater association in these markets. This is something that should be further investigated but, unfortunately, goes beyond the scope of the present study. Finally, the results of the two tailed *t* test indicated a total of 281 statistically significant observations in the conditional correlation time series among the 419 taken into account. This number is considerably lower than those obtained in the previous cases, which raises doubts about the estimated correlation values as they may not be consistent.

The following table provides the results obtained by the main descriptive statistics of the conditional correlation data in each bivariate case studied and Figure 8 illustrates the corresponding time series altogether. The overall picture says that the association between the Brent oil price returns and the Crystal Sugar price returns is the highest among the three cases studied, being this relationship less strong but also significant for the Brent-Soya analysis. The results were considerably low for the association between the crude oil market and the national Brazilian coffee market, however, it should be emphasized that there has been a clearly upward trend in their correlation values particularly after the financial crisis, meaning that the association has grown stronger over the last years.

Table 3. Conditional Correlation - Global Overview

	Studied Cases		
Statistic	Brent-Soya	Brent-Sugar	Brent-Coffee
Mean	0.2376	0.4123	0.2056
Median	0.2541	0.4002	0.2388
Maximum	0.5707	0.9836	0.5538
Minimum	-0.1707	-0.1869	-0.2475
Standard Deviation	0.1224	0.2496	0.1654
Skewness	-0.4870	0.0950	-0.5357
Kurtosis	3.5406	2.6765	2.3999
Jarque-Bera	21.7151	2.4568	26.3260
p-value	0.0000	0.2928	0.0000
Observations	420	419	419
Significant Correlations	300	353	281

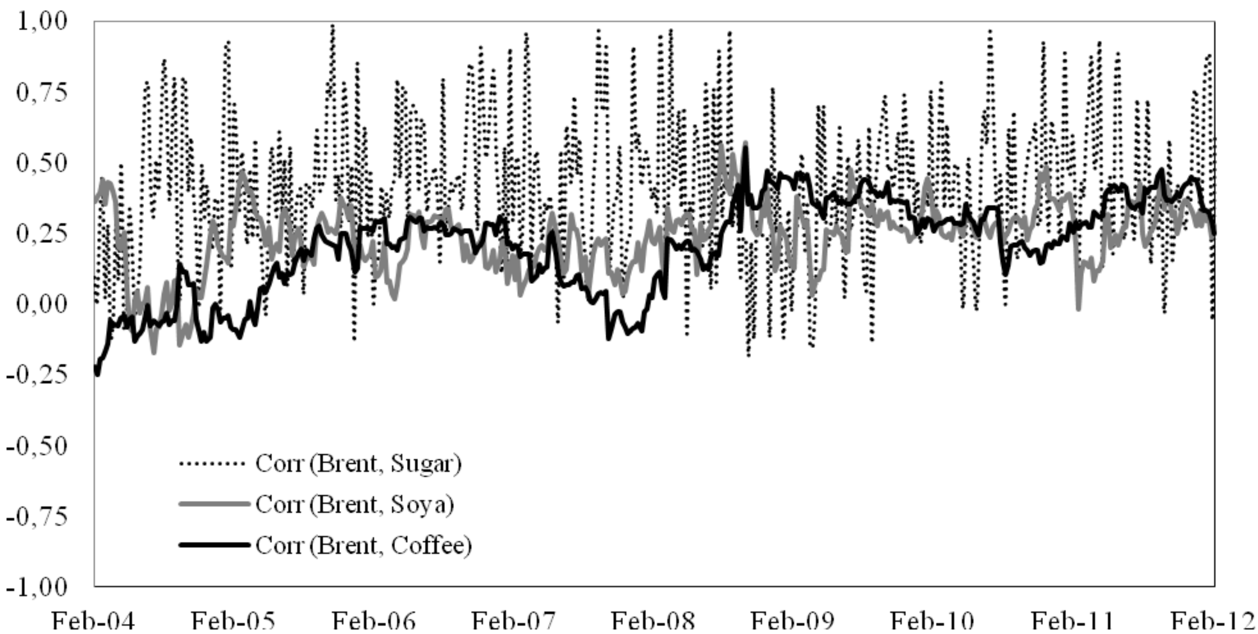

Figure 8. Generated Conditional Correlation Time Series

CONCLUSIONS AND FINAL REMARKS

Taking into account that an estimation of the relationship between oil and food prices is of great importance for the various economic agents such as producers, economists and policymakers, an endeavor has been made to determine the degree of influence of the Brent crude oil market on some specific agricultural commodities markets important to the Brazilian economy. The results were quite satisfactory, considering that national markets, particularly those related to the foreign grain trade may suffer great influence from government policies. As it could be seen in the previous section, there seems to be a solid correlation between the international Brent oil price returns and the returns of the Brazilian Crystal Sugar export price. This relationship is less strong but also significant for the Brent-Soya and Brent-Coffee cases. It was also pointed that, even though the mean value for the generated conditional correlation time series in the Brent and Coffee joint analysis is the lowest among the three cases for the time period of study, there has been a clearly upward trend in these values particularly after the financial crisis, meaning that the association between the crude oil market and the Brazilian coffee market has grown stronger over the last years.

As for the veracity of the information obtained by the estimated models, the results were quite significant when crude oil and sugar prices association was studied and there is no doubt that the estimated values for the dynamic conditional correlation are consistent. The number of significant correlation values was considerably lower for the association between crude oil and soybean price returns and even smaller for the crude oil and coffee price returns association.

Another interest issue was the fact that the markets have shown different behaviors regarding the crisis and after crisis periods. In the first case, the oil and soya markets became more closely associated during the crisis period, end of 2008 and beginning of 2009, as reported by the values obtained for the conditional correlation generated time series. On the other hand, there was a significant decline in these values for the crude oil and crystal sugar prices association during the same period, but later recovering to consistent correlation levels after the crisis. Finally, for the crude oil and coffee analysis, the studied markets have become much more associated than in the past and the correlation values have continued in a positive trend since the last financial crisis. This last particular behavior is something that could be further investigated in future studies, as there may have been some substantial changes in one or both involved markets that could explain the closer association of the Brazilian coffee market with the international crude oil market. Furthermore, it is important to take into consideration in future studies some key factors, such as the seedling cycle, crop and in-between harvest periods and available stocks for all involved agricultural commodities.

In general, the results are quite similar to those from the majority of works that deal with the long-run price relationship between oil and food prices. The positive feedback obtained by the conditional correlation levels in each case studied suggests that the influence of crude oil prices on food prices should be further investigated, even though the Free On Board (FOB) prices of the selected agricultural commodities were used, which somehow limits the generalization of the results to other international markets. It must be pointed out that crude oil prices are paramount for the Brazilian foreign trade, since crude oil is the main Brazilian import product and, as demonstrated in this work, has influence over the prices of the main Brazilian export products.

REFERENCES

Abdel, H. A. and Arshad, F. M. (2008), "The impact of petroleum prices on vegetable oils prices: evidence from cointegration tests", in International Borneo Business Conference on Global Changes: Corporate Responsibility, Malaysia, December, 15-17.

Akaike, H. (1974), "A new look at the statistical model identification", IEEE Transactions on Automatic Control, v. AC-19, n. 6, 716-723.

Bollerslev, T., Engle, R. F. and Woolridge, J. M. (1988), "A Capital Asset Pricing Model with Time-Varying Covariances", The Journal of Political Economy, v. 96, n. 1, 116-131.

Dickey, D. A. and Fuller, W. A. (1981), "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root", Econometrica, v. 49, n. 4, 1057-1072.

Engle, R. F. (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation", Econometrica, v. 50, n. 4, 987-1007.

Engle, R. F. and Kroner, K. F. (1995), "Multivariate Simultaneous Generalized ARCH", Econometric Theory, v. 11, n. 1, 122-150.

Gohin, A. and Chantret, F. (2010), "The long-run impact of energy prices on world agricultural markets: the role of macro-economic linkages", Energy Policy, v. 38, 333–339.

Hannan, E. J. and Quinn, B.G. (1979), "The Determination of the Order of an Autoregression", Journal of the Royal Statistical Society, Series B (Methodological), v. 41, n. 2, 190-195.

Jarque, C. M. and Bera, A. K. (1987), "A Test for Normality of Observations and Regression Residuals", Revue Internationale de Statistique, v. 55, n. 2, 163-172.

Musser, W., Lambert, D. and Daberkow, S. (2006), "Factor influencing direct and indirect energy use in us corn production", in American Agricultural Economics Association Annual Meeting, Long Beach, CA, July, 23-26.

Samuelson, P. A. and Solow, R. M. (1960), "Analytical aspects of anti-inflation policy", American Economic Review, v. 50, n. 2, 177-194.

Schwarz, G. (1978), “Estimating the Dimension of a Model”, The Annals of Statistics, v. 6, n. 2, 461-464.

Udoh, E. (2012), “Does International Oil Price Volatility Complement Domestic Food Price Instability in Nigeria? An Empirical Enquiry”, International Journal of Economics and Finance, v. 4, n. 1, 235-246.