Price Volatility Transmission from Oil to Energy and Non-Energy Agricultural Commodities

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Abstract

The first linkage between oil and agricultural markets is by the production side because of main inputs are oil-intensive (fertilizers). Recently, biofuels likely increased integration between these markets, creating an extra linkage on the demand side. This high integration increases the price volatility transmission, which likely increases uncertainty in agricultural markets. So this paper aims to investigate the integration behavior between these markets in terms of price volatility, checking if there are differences in price volatility transmission from oil to two groups of agricultural commodities: i) energy agricultural commodities (EAC), used in biofuels production; ii) non-energy agricultural commodities (NAC), not used in biofuels productions. In order to do that, we use Mgarch models on monthly basis and found that price volatility transmissions spillovers became stronger for both groups (EAC and NAC), but with opposite directions. EAC returns and Oil returns moved in the same direction over time, and in 2008 this conditional correlation became more positive. Oil and NAC returns moved in opposite direction, and during Financial Crisis conditional correlation became more negative.

Keywords: oil, agricultural commodities, biofuels, volatility transmission, mgarch.

Resumo

O primeiro link entre os mercados agrícolas e o de petróleo é pelo canal da produção, um dos principais insumos são os fertilizantes (intensivos em petróleo). Recentemente a literatura empírica aponta que os biocombustíveis aumentaram a integração entre esses mercados, gerando um link extra. Isso teria aumentando a integração entre esses mercados, aumentando também a volatilidade nos preços das commodities agrícolas. Diante disso, esse artigo tenta observar a integração entre esses mercados no sentido de uma maior ou menor transmissão de volatilidade do petróleo para dois grupos de commodities agrícolas: i) commodities agrícolas energéticas (EAC), amplamente usadas na fabricação de biocombustíveis; ii) commodities agrícolas não energéticas (NAC), não usadas para fabricação de biocombustíveis. Foram usados modelos Mgarch em bases diárias e foram encontradas evidências de que existe transmissão de volatilidade. Os retornos do petróleo e do grupo EAC andaram na mesma direção e essa correlação condicional se tornou mais forte durante a Crise Financeira. Já os retornos do petróleo e do grupo NAC andaram em direções opostas, e a correlação condicional se tornou mais negativa durante a Crise Financeira.

Palavras-chave: petróleo, commodities agrícolas, biocombustíveis, transmissão de volatilidade, mgarch.

JEL: G13, Q14, Q42, Q02.

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1 Introduction

Volatility in agricultural markets increased substantially after 2006. Historical price-demand inelasticity for agricultural commodities is a primary reason to explain high volatility in agricultural prices. It means that, for all prices, quantity demanded is almost the same, so little disruptions in supply need to be accommodated by prices. But, as historical inelasticity should not be pointed as a reason for recent increases, we need to search for new factors to explain that. The literature indicates that the main contributors are:

i. Oil spillovers - linkages with oil market addressed some volatility from oil to agricultural markets (Ji and Fan, 2012; Serra (2011);

ii. Financialization – rising in trading volume assets brought larger price variations (Fleming et. al. 2005)[1];

iii. American monetary policy (Frankel, 2006; Askari and Krichene, 2008; Nazlioglu et. al. 2012);

iv. Macroeconomic factors as increased demand for commodities from China (Gilbert, 2010);

v. Biofuels – marginally increasing demand (Babcock, 2012; Ciaian and Kancs, 2011; Serra, 2011; Hochaman et. al., 2012).

Obviously these factors are not consensus in economics (like almost everything else), but they are the most frequent factor to explain prices volatility in agricultural markets.

Agricultural and oil markets have a well-known linkage given by input markets because fertilizers are oil-intensive. Therefore, we can say that oil prices are one of the agricultural prices determinants in the long run (Serra and Zilberman, 2013). Hence, it is expected that there is some price volatility transmission between oil and agricultural commodities markets.

Part of the empirical literature about commodities prices believes that biofuels have not a significant effect in rising agricultural commodities prices. It is argued that biofuels represent a small market share that cannot cause large demand shifts (Ajanovic, 2011). Another part of the literature claims that market share is small, but because of inelasticities, the effects are leveraged. Even though biofuels are not a consensual reason to explain volatility increases in agricultural markets [2], we found more empirically evidence that they have a role on agricultural commodities prices, as suggested by Babcock (2012), Ciaian and Kancs (2011), Serra and Gil (2012) and Serra (2011; 2013). Hence, there is more evidence that biofuels really produce an extra linkage between commodities and oil markets, and this conclusion is the starting point for our research question.

Therefore, the research question to be addressed is: are there differences in price volatility transmission from oil to agricultural markets in the presence and absence of this extra linkage by biofuels.

In order to answer that, the nine most traded agricultural commodities will be divided into two groups: i) Energy Agricultural Commodities (EAC) – sugar, corn and soybeans; ii) Non-Energy Agricultural Commodities (NAC) – rice, coffee, sunflower, cotton and wheat. The main idea is to test volatility spillovers among these three indexes (Oil, EAC and NAC).

Therefore, the main goals of this paper are twofold: i) to test if there is transmission of price volatility from fossil markets to agricultural markets; ii) to test if there are differences between price transmission of agricultural commodities with direct energy link (soybeans, sugarcane and corn) from agricultural commodities from which this link is based only on the use of fertilizers (coffee, rice, cotton, sunflower and wheat).

In order to answer these questions, conventional Ordinary Least Squares (OLS) approach cannot be applied because of the assumption that residuals are homoscedastic. In a 'homoscedastic world' there is no reason to model volatility, it is just a constant. Hence we use ARCH and GARCH models in a multivariate scenario (MGARCH)[3], which will allow to model volatility including cross volatilities as part of explanation [4].

Using monthly data from January/1989 to May/2013 (293 observations)[5], the results show larger

[1] In this case, correlation between crisis periods and high traded assets would be captured by traded volume (Fleming et. al., 2005).

[2] Ajanovic (2011), for example, says that there is no significant impact of biofuels on feedstock prices.

[3] Multivariate Generalized Autoregressive Conditional Heteroskedasticity.

[4] In this family of models it is allowed that volatilities in one commodity explain the volatility on other commodity.

[5] Monthly spot prices of eight most traded agricultural commodities can be easily found in several databases as Ipeadata, Food and Agriculture Organization (FAO) and Chicago Board of Trade (CBOT).

quasi-correlations parameters for EAC than NAC in price equations, suggesting that oil drives more volatility to commodities with biofuels linkage. Looking at returns equations, EAC has positive quasi-correlations and NAC has negative quasi-correlations, suggesting that Oil and EAC returns moves in the same direction and Oil and NAC returns moves in opposite directions.

This paper has, besides this introduction, a section for literature review about volatility transmission and some facts motivating our study, a section to explain the econometric approach, followed by data and results. Finally, last section is dedicated to the final remarks and comments.

2 Some Facts and Literature Review

Most of time series studies about commodity prices use first moment of regression (mean equation). Although second moment empirical models (volatility equation) are less studied, they are important in economics and it has been evidenced after the Financial Crisis of 2007-2008. The literature on finance was the first area in economics to realize this importance and used second moments in asset pricing models, hedging and risk management. This literature associates more volatility with higher risks and more risks requiring a more profitable expected outcome to be accepted (Bauwens et. al., 2006, p. 79).

Oil is frequently pointed as one of the most volatile commodities. According to Regnier (2007), it is more volatile than 95% of products sold by US domestic producers. This high volatility should have microeconomic implications, as "persistent underinvestment in conservation technology"[6] and optimal requirements choice in industry, and also macroeconomic implications, such as complications in public finance of economies with high oil dependence (both exports and imports). Hence, there are a lot of policies trying to reduce energy price volatilities for consumers and industry. In Brazil, for instance, most of oil refineries belong to Petrobras (government is the major shareholder) that transfers price for consumers in a smoothed way. Around the world, public stocks are also used in attempt to reduce volatility. Biofuels defenders argue that investment in energy alternatives could reduce oil volatility. In a theoretical way, it should happen, but it is not true due to biofuels market being so small (compared with oil) and having so much government intervention.

Agricultural commodities are recognized by short term inelasticity in both demand and supply. Rises in demand usually due to increase in the size of population can be faced by supply adjustments only in the next harvest. Hence, inelasticity hampers adjustment by quantities, driving all adjustment for prices (Cepal, 2011). The period 2006-2008 is called in agricultural prices literature as Food Crisis, which was known by its high peaks in prices. Recently (2011-2012), agricultural prices have been rising again (Graph-1). But in both periods there were more than price increases, there was also increase on prices volatility. Since market inelasticity is a historical characteristic of agricultural markets, we should think in new reasons to understand these recent periods of increasing price volatility.

Agricultural-oil markets integration is pointed as a reason for increases in agricultural prices volatility. A first, and older reason, for this integration is that fertilizers' production is oil-intensive, which implies in some degree of integration by transfer of costs. Second, and more recent reason, is that there is an extra linkage provided by biofuels. This extra linkage is used to divide commodities into two groups in this paper: i) energy agricultural commodities (EAC) – extensively used in biofuels production (sugarcane, corn and soybeans); ii) non-energy agricultural commodities (NAC) – not extensively used in biofuels production (rice, coffee, sunflower, cotton and wheat). It is our belief that this increase in the transmission channel increases volatility in agricultural markets because oil price is more volatile than agricultural prices.

This volatility transmission (oil-agricultural prices) received more attention after the Financial Crisis of 2007-08. The majority of papers claims that there is a clear direction of volatility transmission (from oil to agricultural commodities) and this relationship became stronger recently (mainly after 2006). In other words, we say that these markets became more integrated (Du et. al., 2011; Serra, 2011; Nazlioglu et. al.,2012; Ji and Fan, 2012) and such integration with a market with higher volatility increased volatility in the agricultural prices.

In the case of the role of biofuels in prices, IMF estimated that 70% of marginal increase in corn prices and 40% of soybean prices were caused by demand expansion for biofuels (Ciaian and Kancs, 2011, p. 327). OECD-FAO (2013) considered biofuels the main reason for food inflation in the past decade. On

[6]High price volatilities are associated with high market risks. Hence, for energy prices, high volatility is pointed as a cause of low investment in energy conservation and energy alternatives (Regnier, 2007).

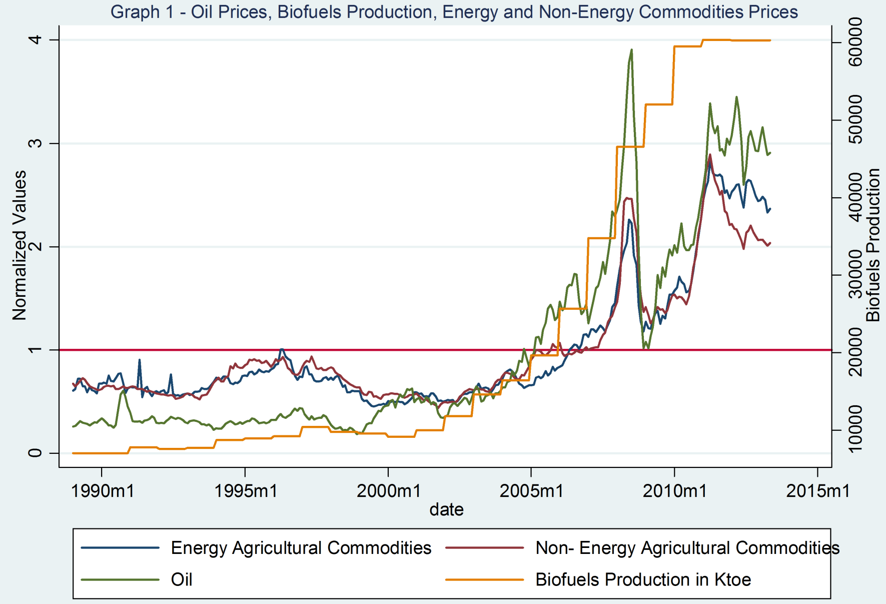
the other hand, some authors say that biofuels can be responsible only for marginal effects in prices, but not for the total effects (Aijanovic, 2010). Since only 1% of world's agricultural land is used for biofuels production, they would not have enough power to shift demand. Both assumptions are feasible, but literature widely agrees that biofuels have an effect, at least marginal, in rising agricultural commodities prices. Because of supply inelasticity, marginal effects in demand can be magnified, causing large effects in prices.

Even if competition is only marginal, biofuels compete with food for land, and this competition does not depend if production is based on food or non-food crops. In Brazil, for example, 55% of sugarcane production was allocated to ethanol production, and in the USA this proportion was around 40% of corn production, both considering the harvest for 2010-2011 (Serra and Zilberman, 2013, p. 141). Considering the world production, the proportion used for ethanol production falls to 15% of corn and 18% of sugarcane (Daynard and Daynard, 2011).

In Graph-1 it is possible to see a clear positive correlation among biofuels production and commodities prices. However, it can lead to say from this correlation that biofuels represents a true and/or only determinant in the commodity prices, which is likely a mistake. There are many correlated effects with expansion of biofuels production. The increases on oil price volatility and agricultural prices volatility are positively correlated with biofuels production. Hence, when empirical estimations consider only biofuels, omitting other effects positively correlated, they are likely overestimating the biofuels effects. According to Oladosu and Msangi (2013, p.54), recent papers are actually revising biofuels effects in the way to reduce the role of biofuels in agricultural commodities inflation.

Also in Graph-1, it is possible to see that all three series (Oil index, EAC and NAC) are above

Graph 1 - Oil Prices, Biofuels Production, Energy and Non-Energy Commodities Prices



Source: Authors with prices from Ipeadata and biofuels production from BP (2013)
Notes: * Y=1 is a reference line; ** Biofuels production is on annual basis.

their historical averages (considering our sample). Series are normalized, and values above reference line are indicating prices above period-average. Biofuels production seems to have successive breaks because data are on annual basis, while other series are based on monthly data.

Agricultural markets have expected responses: high prices indicate increasing supply in the next periods and low prices indicate a decreasing supply (OECD-FAO, 2013, p.13). In this context, high prices cannot drive to long run shortage, because of expected supply adjustment. But as Mitchell (2009) suggests, high prices associated to high volatility increase market uncertainty and could drive to food insecurity due to the less than optimal investment volume in high uncertain scenario.

There is need to be cautious about the claim of a tradeoff between biofuels and food insecurity, as suggested by Cepal (2011), Serra and Gil (2012) and OECD-FAO (2013). This is so because biofuels production occurs in food-secure regions (US, Brazil and Europe), so for biofuels to increase food insecurity there would be necessary to have the assumption that saved crops in food-secure regions can be hunger-minimizer in food-insecure regions. But this is not feasible, since geographic distances prohibit this trade. Then, the alternative that biofuels are causing hunger could be through price transmission. However, regions that are suffering by hunger are so economically isolated that this transmission is far to be an issue (OECD-FAO, 2013, p. 55).

Literature about price transmission in agricultural markets is large and an extensive review can be found in Serra and Zilberman (2013). Authors also bring a review on empirical estimations of commodities prices volatility. Vector error-correction models (VECM) of Engle and Granger (1987) changed the way to study price transmission, allowing for short and long run interactions, and giving a better statistical treatment for non-stationary series, becoming the workhorse of price transmission studies.

Similar changes occurred with Autoregressive Conditional Heterocedastic (Arch) models, also proposed by Engle (1982) in study about volatility. Seminal Arch models were not fully able to model volatility transmission because they model volatilities using just the own past volatilities. More recent developments, such as Garch-in-mean and Mgarch models, allowed better specifications of volatility transmission.

About this issue on agricultural markets, Busse et. al. (2010) studied volatilities in agricultural commodities using an Mgarch model in returns of rapeseed and crude oil. Using daily dataset (1999 to 2009) they found an increasing correlation between rapeseed and oil prices, indicating a high integration between these two markets and closer responses from rapeseed market to oil market fluctuations.

Serra et. al (2011) studied transmission among oil, ethanol and sugar prices on weakly basis (2000 to 2008) and found that increases in oil prices contributed to ethanol markets to achieve higher equilibrium prices, while they caused just short run instability in sugar prices, driving some volatility. They used a Seo's method that includes an estimation using VECM in mean equation and Mgarch for volatilities.

Nazliouglu et. al. (2013) investigated price volatility spillovers between oil and selected agricultural commodities (wheat, corn, soybeans and sugar) on daily basis (1986 to 2011). They used univariate Garch and causality tests. Their results indicated that food crisis increased the link between oil price and agricultural markets. Before the crisis, there was no price transmission from oil to agricultural markets, but after the food crisis there were some transmission in corn, wheat and soybeans markets. Sugar market seems to not respond to oil shocks. The data break for the food crisis was 2005.

Assuming that there is price volatility transmission from oil to agricultural commodities, we will test if there are differences in this transmission between EAC and NAC. Since EAC have a larger linkage with oil markets, it is expected that the transmission should be also larger.

3 Econometric Approach

In conventional models, variance of disturbance term is assumed to be constant. But it is not true for many time series, especially when there is some break or structural change that likely altered volatility parameters (Enders, 2004, p. 111). In price series, for example, observations with high volatility are commonly followed by high volatility observations, and this clustered behavior is also founded in low volatility periods (Franses, 1998, p.24). The empirical verification of this implies that the majority of econometric models cannot be applied because of the assumption of homoscedasticity, suggesting the use of models that allow conditional heteroscedasticity[7]. Considering a common first moment regression:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t \tag{1}$$

In order to the OLS to be a BLUE estimator, $Var(\varepsilon_t \mid X_t)$ needs to be constant. One of the first models that tried to relax this assumption was the Autoregressive Conditional-Heteroscedasticity (Arch) model from Engle (1982) that modeled the second moment of regression as an Arch (q):

$$E(\varepsilon_t^2 \mid \varepsilon_{t-1}) = H_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{2}$$

In order to allow just positive conditional variances, α_0 and α_1 are both larger than zero. Note that the expected variance is an equally weighted average of squared residuals from the past, and these weights will be estimated as parameters of the model, choosing the best weights to forecast the variance

[7]Financial crisis in 2007-08 is a clear source of increasing volatility in commodities prices and is pointed as one of reasons for increasing the use of time-varying volatility models (Aielli and Caporin, 2013).

(Engle, 2001, p. 159). The generalization of this model is a Generalized Autoregressive Conditional-Heteroscedasticity (Garch (p, q)) that includes also lagged H_t:

$$H_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i H_{t-i}{}^{8} \tag{3}$$

In the GARCH specification, as proposed by Bollerslev (1986) in his model, all parameters are restricted to be larger than zero. The idea behind Equation (3) is that a mix between long run variance (β) and variance in recent periods (α) is a good predictor of next period's variance. The evolution of GARCH models is the generalization of univariate case in direction to a Multivariate Generalized Autoregressive Conditional-Heteroscedasticity (Mgarch). The generalization for the covariance matrix **H** for a Mgarch (1,1) is usually expressed by:

$$vech(H_t) = C + \alpha vech(\varepsilon_{t-1}\varepsilon_{t-1}') + \beta vech(H_{t-1}) \tag{4}$$

Where vech is the column-staking operator of the lower portion of a symmetric matrix[9] and α, β, and **C** are matrix coefficients. The first problem to apply full *vech* in Mgarch models is the fast increasing of the parameters. Just with three series the number of coefficients in a full *vech* generates 78 parameters. It caused the need for re-parameterization to estimate Mgarch (Silvernnoinen and Teasvirta, 2008, p. 2). Another reason to impose restrictions to H_t is to guarantee that it is positive definite. The variance and covariance matrix for a unique component vech-diag in a bivariate case (commodities 1 and 2) is expressed by:

$$\begin{pmatrix} H_t^{11} \\ H_t^{12} \\ H_t^{22} \end{pmatrix} = \begin{pmatrix} C_0^{11} \\ C_0^{12} \\ C_0^{22} \end{pmatrix} + \begin{pmatrix} \alpha_1^{11} & 0 & 0 \\ 0 & \alpha_1^{21} & 0 \\ 0 & 0 & \alpha_1^{22} \end{pmatrix} \cdot \begin{pmatrix} \epsilon_{t-1}^1 . \epsilon_{t-1}^1 \\ \epsilon_{t-1}^1 . \epsilon_{t-1}^2 \\ \epsilon_{t-1}^2 . \epsilon_{t-1}^2 \end{pmatrix} + \begin{pmatrix} \beta_1^{11} & 0 & 0 \\ 0 & \beta_1^{21} & 0 \\ 0 & 0 & \beta_1^{22} \end{pmatrix} \cdot \begin{pmatrix} H_{t-1}^{11} \\ H_{t-1}^{12} \\ H_{t-1}^{22} \end{pmatrix} \tag{5}$$

Note that Equation (5) does not allow for cross-volatility, since all elements out-off principal diagonal are equal zero (Wang and Wu, 2012, p. 2169). So the volatility of commodity 1 is determined just for its own past volatility and its own cross-product of error term. Remember that our question is "how oil drives volatility to energy and non-energy agricultural commodities", so we need to compute the volatilities spillovers. Hence, we need to use a model to allow for a richer dynamic in volatility as BEKK[10], CCC or DCC models[11]. Among the possible models we will use here are the Constant Conditional Correlation (CCC) and the Dynamic Conditional Correlation (DCC).

The CCC models are specified in a hierarchical way, and at first a GARCH is chosen for conditional variance (for each one, if there are 10 series, it is possible to have one process for each of the series). Second, with the results of conditional variance, it is specified the conditional correlation matrix (Bauwens et. al., 2006, p. 88). It is important not to consider conditional covariance as conditional correlation. In CCC, conditional correlation is constant, but the conditional covariance "move just enough to keep correlations constant" (Engle, 2009, p. 37). In CCC model it is expressed by:

$$H_t = D_t R D_t = \rho_{it}\sqrt{h_{iit}h_{jjt}} \tag{6}$$

Where,

$$D_t = diag(\sqrt{h_{11t}} ... \sqrt{h_{nnt}}) \tag{7}$$

In Equation (6), R is a positive definite matrix with constant conditional correlations ρ_{it} where the principal diagonal has all numbers equal to one. The CCC models were proposed by Bollerslev (1990) and, from his model, Engle (2002) proposed a DCC model. Note that in DCC model R matrix is time-dependent:

$$R_t = diag(q_{11t}^{\frac{-1}{2}} \cdots q_{nnt}^{\frac{-1}{2}}) Q_t diag(q_{11t}^{\frac{-1}{2}} \cdots q_{nnt}^{\frac{-1}{2}}) \tag{8}$$

[8] In order to find the variance in the long run, the variance of steady state, we need to calculate $H = \alpha_0/(1 - \alpha_1 - \beta_1)$. If $\alpha_1 + \beta_1 = 1$, the long run variance cannot be estimated and it is necessary to use an Integrated Garch (Igarch) (Nelson, 1990; Margarido, Azevedo and Shikida, 2012).

[9] Considering a symmetric matrix A (2x2) $= \begin{pmatrix} a_{11} & a_{11} \\ a_{21} & a_{22} \end{pmatrix}$, as $a_{12} = a_{21}$, the $vechA = \begin{pmatrix} a_{11} \\ a_{12} \\ a_{22} \end{pmatrix}$.

[10] Baba, Engle, Kraft and Kroner Mgarch, for more information see Baba et. al. (1990).

[11] For more information see Bauwens et. al. (2006), Silvernnoinen and Teasvirta (2008) and Engle (1982; 2002).

Where,

$$Q_t = (1 - A - B)\overline{Q} + A\varepsilon_{t-1}\varepsilon'_{t-1} + BQ_{t-1} \tag{9}$$

and because R is now time-dependent, Equation (6) becomes:

$$H_t = h_{ijt} = D_t R_t D_t = \rho_{ijt}\sqrt{h_{iit}h_{jjt}} \tag{10}$$

Then, the diagonal elements in (9) are modeled as univariate GARCH, and the elements off-diagonal are nonlinear functions of diagonal terms. In DCC the matrix D_t will be the same as reported in (7), with all elements off-diagonal being equal zero. In a study with 3 variables (as ours) D_t will be:

$$D_t = diag(h_{1t}^{\frac{1}{2}}, h_{2t}^{\frac{1}{2}}, h_{3t}^{\frac{1}{2}}) = \begin{pmatrix} h_{1t}^{\frac{1}{2}} & 0 & 0 \\ 0 & h_{2t}^{\frac{1}{2}} & 0 \\ 0 & 0 & h_{3t}^{\frac{1}{2}} \end{pmatrix} \tag{11}$$

Where each conditional covariance can have a constant, an Arch term and a Garch term, as in Equation (3).

The parameters A and B (Equation 9) need to be positive and respect the restriction $A + B < 1$. $\overline{Q}$ is the matrix with unconditional variance of the series. Even using one of the most flexible models to measure volatility, there still are restrictions. The most obvious restriction comes from the fact that A and B are scalars numbers and not matrix, implying that all series have the same dynamics[12]. The matrix Q_t could be seen as an ARMA process capturing the short run dynamics (Hernandez and Robles, 2013, p. 8) and $\overline{Q}$ is the long run forecast of variance (Enders, 2004, p. 112).

If $A = B = 0$, the model used should be the CCC model. In other words, there is no evidence that correlations are time-varying. In the case of restriction $A + B < 1$, it is necessary to ensure that the model will be stationary. If $A + B = 1$, the model is still stationary, but just "weakly stationary" (Engle, 2002). With $A + B = 1$ we have an Integrated Mgarch. So, there are three main possibilities to quasi-correlations: a mean-reverting process, an integrated process and an asymmetric process (Engle, 2009). In this study we will explore the mean-reverting possibility. Note that, the first step, estimating the conditional variance, allows for different processes and here we consider the possibility of this step to be integrated. But, for quasi-correlations we will explore just the mean-reverting process.

4 Data and Unit Root Tests

The economic series used in this paper are the spot prices on monthly basis for oil, sugar, cotton, soybean, coffee, corn, sunflower, rice and wheat. The series can be easily found on different databases such as Ipeadata, Food and Agriculture Organization (FAO) and Chicago Board of Trade (CBOT). Prices to international trade are in US dollars, and to get the spot prices in real prices we used the Consumer Price Index for All Urban Consumers from Bureau of Labor Statistics. The series are from January/1989 to May/2013 (293 observations).

We defined energy agricultural commodities as those commodities that, in addition to have a supply link with oil market through the use of fertilizers, have also a demand link by biofuels production. Hence, sugar, corn and soybean are used to create the Energy Agricultural Commodities Index (EAC). EAC index is the result of geometric average of sugar, corn and soybean indexes. The non-energy agricultural commodities (NAC) were defined as agricultural commodities that have just the first link (fertilizers) with the oil market. Therefore, the other commodities that are used to construct the NAC Index are: cotton, coffee, sunflower, rice and wheat. Table 1 illustrates the summary statistics for these data.

The variables need to be stationary to be included in the MGARCH models. Using just first generation unit root tests, Augmented Dickey-Fuller (ADF) and Philips Perron (PP) tests, in the presence of structural change, there is a "potential confusion of structural breaks in the series as evidence of nonstationarity" (Baum, 2001, p.9). In other words, ADF and PP are biased in direction to wrongly accept the null of existence of unit root in presence of non-linear trends. Since our sample is from January/1989 to

[12]It is possible to give particular dynamics to each of the series attributing to them scalars α and β in the matrix of parameters, but again, there is a tradeoff between number of parameters and model flexibility.

Table 1: Summary Statistics for the variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Real Prices					
Oil	293	41.88	31.58	10.41	132.55
Coffee	293	107.48	49.00	37.67	270.30
Cotton	293	73.00	25.65	37.22	229.67
Corn	293	139.49	63.44	75.06	332.95
Rice	293	338.63	148.85	162.10	1015.21
Sugar	293	12.95	5.19	5.68	27.61
Sunflower	293	803.96	391.89	332.55	2300.19
Wheat	293	183.62	70.05	102.16	439.72
Soybean	293	625.05	264.73	321.40	1414.40
Price Index					
EAC Index	293	0.42	0.27	0.19	1.20
NAC Index	293	0.49	0.28	0.21	1.39
Oil Index	293	0.34	0.33	0.06	1.34
Return Index					
Oil Return	293	0.00	0.09	-0.37	0.48
EAC Return	292	0.00	0.06	-0.37	0.24
NAC Return	292	0.00	0.04	-0.22	0.22

Source: Data from Ipeadata, FAO and CBOT. Author's calculations.

May/2013, we need to test that for the possibility of structural breaks.

Beyond confusion (structural breaks-unit roots) ADF and PP also have a binary restricted option for I(d): I(1) or I(0). But, as pointed by Banerjee and Urgh (2005), the empirical literature of time series has been walking in the direction of not simply testing an I(1) null against an I(0) alternative hypothesis, but in direction to allow fractionated values for I(d). In this sense, unit roots and stationary processes are just special cases of fractional integration where 'd' is respectively 1 and 0.

Therefore, a lot of integrated series are being revised in direction on having a long memory process (d>0.5) instead of I(1) process (Banerjee and Urgh, 2005). Other reason to suppose that series are not I(1) is the persistency of shocks, if series are a true I(1), such that shock effects will never die. Rapport and Reichlin (1989) and Perron (1989) argue that the most part of shocks in economy is transitory and not permanent.

New findings about integration order in time series requires for a revision in procedures. Previously, cycles were understood as the sum of a secular trend (linear) and a cyclical component (stationary), and it spreads and justifies the use of filters and differentiated series. Nelson and Plosser (1982) were the first to consider that "stochastic nature of the trend should be considered" (Banerjee and Urga, 2005, p.3). Hence, procedures were revised in sense that mechanical use of ADF and PP (test the series $\rightarrow$ reject the null of stationarity $\rightarrow$ use series filtered or differentiated) are not indicated. This approach frequently confuses uncounted breaks and long memory processes with unit root process.

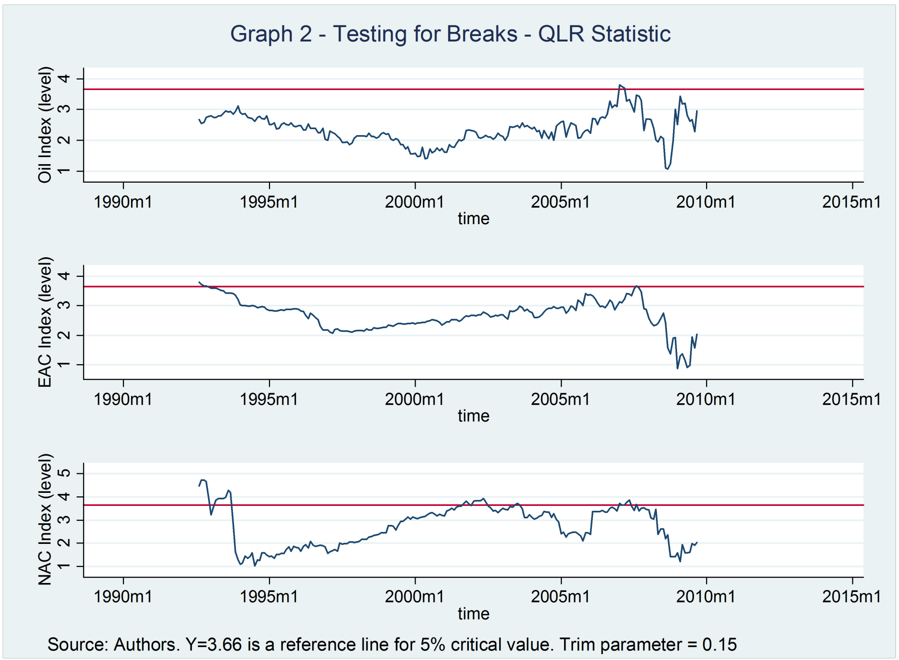
Granger and Hyung (2004)[13] indicate a procedure that consists of three basic steps: i) estimation of 'd' by GPH test; ii) investigation about breaks; iii) considering the breaks, 'd' is estimated again. This procedure attempts to distinguish between unit roots, long memories and breaks. Only when $d = 1$, after accounted for breaks, that we can be sure that a time series is I(1).

We will use QLR test proposed by Quandt (1960) and revised by Andrews (1993)[14] to investigate breaks presence. This is a modified version of Chow test for unknown breaks. Here we did not suppose a specific date for break, and the test is done recursively. The QLR test results are plotted in Graph-2, where points above the reference line indicate the presence of breaks.

[13] An interesting empirical use of this method for the Brazilian economy can be found in Silva and Vieira (2013).

[14] More information about critical values are found in Andrews (1993, p. 840, Table 1). There is a correction for values in Andrews (2003), but values are very similar, with exception for eight degrees of freedom. Note also that values in Table 1 in Andrews (1993) still need to be divided by $q = 5$ (in our case, four lags and the constant used in tests). Therefore we use 3.66 and not 18.35.

QLR tests showed a similar pattern considering the Financial Crisis of 2007-08 as a break in three



series. Trim parameter of 0.15 means that 15% of sample in each extreme was discarded, which is the default procedure because of the test is biased by initial and final values, and the bias goes in the direction to consider breaks that actually do not exist. For this reason, we did not consider the EAC and NAC first breaks (around 1992:m8) as a true break. NAC was the only one among the three series that we will considerer having two breaks: one in 2007:m1 and another around 2002:m1. QLR statistic does not qualify the type of break, so we tested the possibility of four lags and the constant, and then we cannot decide if the break is in the intercept, in the trend or in both. Finally, a filter is used in the series considering the possibility of break in intercept, in trend and in both possibilities (intercept and trend).

After these diagnostic tests about the presence of breaks, we test a modified version of Geweke and Porter-Hudak (1983) or (GPH test) proposed by Phillips (1999), called here as Phillips' modified LPR[15]. Phillips (1999) argues that original GPH is inconsistent for $d > 1$. We test that in the original series (Y_t) and in filtered series $(Y_t - Z_t)$, where Z_t is the vector of breaks. Considering an intercept break, Z_t is 1 if $t > t_b$, and 0 otherwise. Considering a trend break, Z_t have values $t - t_b$ if $t > t_b$, and 0 otherwise. For this test we have two important null hypothesis ($d = 0$ and $d = 1$), and Table 2 brings these results.

Table 2 indicates that data generating process of our indexes are not explosive, especially when breaks are considered. In two indexes (Oil and NAC) we cannot reject the null of $d = 0$ and strongly rejected the null of $d = 1$. In other words, we are far from a unit root process ($d = 1$), and it is possible that processes are stationarity, especially when breaks are considered.

In the returns series we also need to test the possibility of breaks for a better specification of mean equation in Mgarch models. In this case there is no issue about confusing the presence of breaks and unit root, since returns are recognized as being stationary processes. Therefore, we proceed the QLR test investigating breaks in returns series (Graph-3).

The series of returns followed the same pattern seen for the series of prices, with a break around the Financial Crisis 2007-08. The more relevant spike detected was around 2007:m1 for prices, and for returns the main spikes were around 2008:m1. So, the break for the returns due to Financial Crisis will be 2008:m1 and not 2007:m1. NAC returns also showed two breaks as NAC level prices.

Mgarch models are indicated when there is evidence of conditional heterocedastic effects in residuals of mean regressions. Considering that a simple AR(2) process is a good specification for series (means) of prices and plotting squared residuals (figures are in appendix), brings the possibility of cluster volatility. We estimated the mean equation of returns using just a constant term. Plotting these squared residuals (not reported here) also brought the possibility of cluster volatility hypothesis in returns series.

A visual inspection of squared residuals should not be a substitute for a formal test (Enders, 2004,

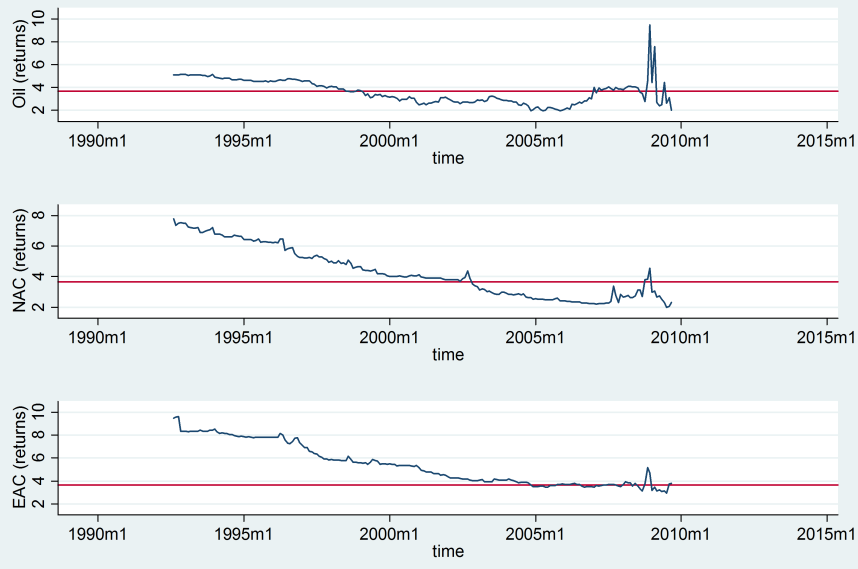
[15] Abbreviation for Log Periodogram Estimator.

Table 2: Phillips' modified LPR test for fractional integration (d)

	Yt	Yt-Intercept	Yt-Trend	Yt-Both
Oil Index (Level)	0.3554	-0.0214	0.6239	0.3169
Std. Err.	0.1675	0.1777	0.0672	0.0704
Ho(d=0) (t)	2.1220**	-0.1205	9.288***	4.5011***
Ho (d=1) (t)	-4.1448***	-6.5672***	-2.4182**	-4.3918***
EAC Index (Level)	0.7647	0.4752	0.4528	0.3232
Std. Err.	0.1803	0.1016	0.1460	0.1293
Ho(d=0) (t)	4.2419***	4.6789***	3.1014***	2.5006**
Ho (d=1) (t)	-1.5131	-3.3744***	-3.5182***	-4.3513***
NAC Index (Level)	0.5184	0.0377	0.2583	0.0339
Std. Err.	0.2536	0.1967	0.2208	0.2759
Ho(d=0) (t)	2.0443*	0.1919	1.1697	0.1231
Ho (d=1) (t)	-3.0959***	-6.1868***	-4.7685***	-6.2111***

Source: Data from Ipeadata, FAO and CBOT. Author's calculations following procedure proposed by Granger and Hyuong (2004). Notes: a) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. b) Tests for breaks done using QLR statistics, so for all series we used a dummy in 2007:m1 and for NAC series we used an additional dummy in 2002:m1.c) Intercept is a "classic dummy" and trend dummy is an additive dummy, trying to capture a more gradual break.

Graph 3 - Testing for Breaks - QLR Statistic - Returns



Source: Authors. Y=3.66 is a reference line for 5% critical value. Trim parameter = 0.15

p. 111). A test widely used in the presence of Arch effects was proposed by Engle (1982). In order to do the test it requires getting the squared residuals of the mean equation and regressing them against a constant and their lagged values. If the coefficients of lagged values are different from zero (following a chi distribution), there are Arch effects. Tests' results are in Table 3.

Table 3: Lagrange Multiplier Test for Arch effects (Ho: no Arch effects)

Series	Lags (p)	Chi2	Prob
EAC Index (Return)	0	34.56	0.00
EAC Index (Level)	2	49.57	0.00
NAC Index (Return)	0	41.56	0.00
NAC Index (Level)	2	50.39	0.00
Oil Index (Return)	0	45.09	0.00
Oil Index (Level)	2	117.51	0.00

Source: Author's calculations. Notes: LM Test proposed by Engle (1982). We tested all these series considering structural breaks and concluded that, even with breaks, Arch effects remained in the residuals. Test was repeated with several lags providing the same results.

Formal tests confirm the visual inspection showing strong evidence of cluster volatility, indicating the need for conditional heteroscedasticity specification to model volatilities. In all series tested, the null hypothesis of no Arch effects was rejected.

5 Results

We proposed an AR(2) process for mean equations and ARMA(1,1) process for volatility equations, for both price models, CCC and DCC, using both Arch and Garch terms. The choice of AR(2) was based on partial autocorrelation functions (not reported here). Following QLR results, relevant breaks were included in the mean and variance equations.

For the series of returns, the mean equations were modeled by a constant plus breaks. There is no reason to believe that an AR(p) is a good predictor for returns because of the efficient market hypothesis[16]. The volatility equations for returns have the same specification used for the price equations, that is, a Garch (1, 1).

For a better visualization this section is divided into prices results and returns results. This follows a discussion about some results implications, where we try to compare our results with the empirical literature about commodities prices.

5.1 Prices

It was expected that oil index would transfer volatility to commodity prices. In our model it is represented by positive cross-volatility for both agricultural commodities indexes prices (NAC and EAC)(Q. Corr. in Table 4). More than just positive signs, we also expected that cross-volatility for EACp had larger signals than the one for NAC, indicating that markets with larger links (energy agricultural commodities) will have larger volatility transmissions. Mean equations need to respect stability conditions of AR(p) process, the sum of lagged variables should not exceed one to guarantee that process is mean reverting. This condition was guaranteed for all three series.

In the Oil mean equation, the sum of AR(p) parameters is around 0.96, indicating high persistence of level prices. Intercept dummy for 2007 is highly significant for mean and for variance equation, indicating that 2007 has a positive jump in price and in volatility. Specification in Table 4 was the best fitted model, so we already removed 2002 dummy from oil mean equation and it was added in the volatility equation.

The estimated parameters for EAC and NAC mean equations were also of high persistence. The

[16]Efficient market hypothesis (EMH) says that price market reflects the public available information. Hence, there is no space for a consistent AR(p) process to describe returns. Recently two professors were laureate with Nobel Prize exactly claiming in favor of EMH (Eugene Fama – Chicago University) and against EMH (Robert Shiller and Lars Hansen – Yale University). A survey about that can be found in Beerchey et. al. (2000) and in Hansen (2013).

positive and significant intercept dummies indicate positive increases in prices.

In the case of long run volatilities, as expected, oil showed higher volatilities than the other two indexes (NAC and EAC). In the calculation of the long run variances in the first period (before the first break) we found long run variances around 50 (oil), 27 (NAC) and 7 (EAC)[17]. Note that positive and significant breaks in volatility are indication that long run volatility changed over time. For oil, for example, the long run volatility was 50 until 2002:m1, approximately 84 (70%more if compared with first period) between 2002:m1 and 2007:m1, and 102 from 2007:m1 until the end of the sample (106% more when we compare with first period).

It is important to stress that in the volatility equation the moving average term (α) indicates the last period volatility impact (once we use just one lag in the Arch term) and that the autoregressive term (β) indicates the persistence or the role of long run variance in variance forecast. The share between Arch and Garch are also the same in all volatility series; the weight between long run and last period is almost the same, but the magnitude of persistence ($\alpha + \beta$) showed large persistence in volatility Oil and NAC (around 0.9), and little persistence in EAC series (around 0.43).

[17] Long run variance is calculated by $H = const/(1 - \alpha - \beta)$. So, for oil's long run volatility before 2002 we solve $H = 2.986/(1 - 0.536 - 0.404) = 49.76$. Note that intercept dummies are added up to the constant in the calculations for the following periods.

Table 4: Results for CCC and DCC using Price series

	CCC		DCC	
Variables	Coef.	Int. Coef.	Coef.	Int. Conf.
Oil				
L.Oil	1.250***	[1.130,1.371]	1.263***	[1.148,1.378]
L2.Oil	-0.299***	[-0.419,-0.180]	-0.314***	[-0.428,-0.199]
DI2007	42.28***	[20.58,63.97]	42.79***	[20.04,65.55]
_cons	5.999***	[2.617,9.380]	6.255***	[2.787,9.722]
ARCH_Oil				
Arch (α)	0.404***	[0.193,0.615]	0.363***	[0.156,0.570]
Garch (β)	0.536***	[0.365,0.707]	0.563***	[0.381,0.746]
DI2002	2.063***	[1.074,3.051]	2.219***	[1.201,3.237]
DI2007	1.117	[-0.123,2.356]	1.707**	[0.604,2.810]
_cons	2.986***	[2.125,3.848]	2.831***	[1.869,3.793]
EAC				
L.EAC	1.019***	[0.876,1.162]	1.037***	[0.911,1.162]
L2.EAC	-0.0492	[-0.189,0.0911]	-0.0670	[-0.191,0.0570]
DI2007	8.056*	[1.750,14.36]	7.299*	[1.315,13.28]
_cons	3.606*	[0.726,6.487]	3.885**	[1.244,6.527]
ARCH_EAC				
Arch (α)	0.212**	[0.0798,0.344]	0.206**	[0.0762,0.336]
Garch (β)	0.277	[-0.0105,0.565]	0.226	[-0.0717,0.524]
DI2007	1.386***	[0.903,1.869]	1.864***	[1.381,2.347]
_cons	3.362***	[2.869,3.855]	3.411***	[2.932,3.891]
NAC				
L.NAC	1.330***	[1.208,1.452]	1.279***	[1.158,1.400]
L2.NAC	-0.359***	[-0.480,-0.237]	-0.311***	[-0.432,-0.189]
DI2007	5.962***	[2.837,9.087]	6.082***	[2.823,9.340]
_cons	2.738***	[1.246,4.230]	3.083***	[1.514,4.651]
ARCH_NAC				
Arch (α)	0.433***	[0.227,0.639]	0.532***	[0.276,0.789]
Garch (β)	0.454***	[0.258,0.650]	0.397***	[0.165,0.630]
DI2007	2.043***	[1.289,2.797]	2.453***	[1.656,3.249]
_cons	1.041**	[0.300,1.783]	1.180**	[0.318,2.042]
Q.corr(Oil, EAC)	0.277***	[0.164,0.390]	0.929	[-1.103,2.961]
Q.corr(Oil, NAC)	0.263***	[0.149,0.377]	0.856	[-1.170,2.882]
Q.corr(NAC, EAC)	0.429***	[0.330,0.527]	1.213	[-0.930,3.357]
Adjustment				
lambda1			0.0435**	[0.0163,0.0707]
lambda2			0.951***	[0.915,0.987]
N	291		291	
AIC	6414.7		6383.4	
BIC	6517.5		6493.6	

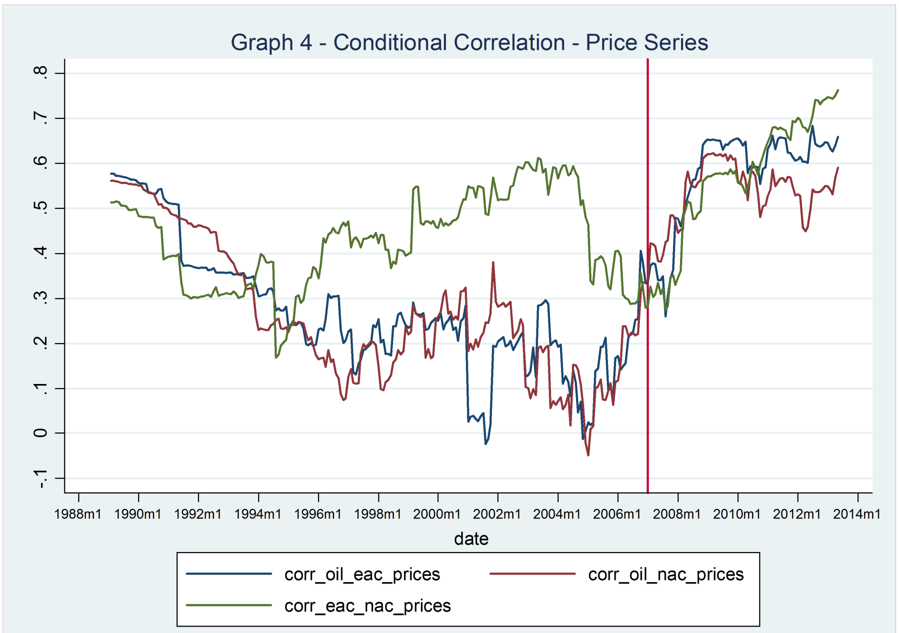
Source: Authors. Mean Equation: $Y = AR(2)$; Variance Equation $H_t = w + \alpha.Arch + \beta.Garch + \epsilon$. Notes: a) 95% confidence intervals in brackets; b) * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001.

For the first estimates (without breaks – not reported) both models, CCC and DCC, for all three series, suggests an Igarch process ($\alpha + \beta = 1$), where shocks in volatility are not dissipated. Franses (1995) and Lamourex and Lastrapes (1990) highlights the possibility of overstated variances if structural shifts are not taken into account in the model, what would cause the wrong impression that shocks are permanent. Recently, Hillerbrand (2005) treated the same problem and says that omitted variables in the variance equation makes Garch models strongly biased in the direction that parameters sum to one

(Igarch). After considering breaks in both equations, the process became mean reverting[18].

According to the estimated quasi-correlations, there is some evidence that oil prices transfer more volatility to energy agricultural commodities. In both models (CCC and DCC), the parameters of quasi correlations are larger for EAC than for NAC. In a general sense we can say that oil increases both volatilities for NAC and EAC, and this relation is statistically significant. There is a positive volatility transmission between NAC and EAC (Q. Corr (EAC, NAC)) and this transmission is larger than the other two relationships, which is expected, since there should be more transmission within agricultural markets than from oil market to agricultural markets.

Lambdas 1 and 2 in Table 4 are the adjustment parameters of conditional covariances in DCC model. This is also an ARMA(p,q) process where lambda 1 is lagged values (q) and lambda 2 represents autoregressive term (p). Hence, a larger lambda 2 is indicating that past values have more importance than lagged residuals innovation (Baum, 2013). The fact that these values are statistically different than zero can be evidence that conditional covariances are time-varying. In other words, DCC is more indicated than CCC model. Note that we have just used one proportion between lagged residuals and residual innovations and three quasi-correlations. Summing up, the same process is imposed for three quasi-correlations, which is a limitation of the model (Engle, 2002).



Source: Authors using results from DCC model. X = 2007m1 is a reference line for Financial Crisis

These quasi-correlations reported (Table 4) are the mean of the period, so it is impossible to see the behavior of parameters by time. In order to check this we plotted conditional correlation between pairwise of series (Graph-4)[19]. The results are indicating that these series are moving in the same direction and, more than this, the degree of correlation increased in recent periods, mainly after the Financial Crisis 2007-08. The conditional variance for each index EAC and NAC also increased, as expected (not reported here).

5.2 Returns

For the series of returns (P_t/P_{t-1}) we did not expect a good fit for the models estimated as mean equations because of hypothesis that markets are efficient. It is usual in the literature to model series of returns as a random walk process, using just a constant in the mean equation, which is the specification

[18]In an ARMA (p,q) process, to ensure that variable has a mean-reverting behavior the condition $(p+q) < 1$ need to be respected. The equivalent condition for volatility equation is that $(\alpha+\beta) < 1$. If it is not valid, it would lead to an explosive data generating process.

[19]The output from 'predict' in Stata.12 is conditional covariance and not conditional correlation. We calculated correlation using $Corr(X,Y) = Cov(X,Y)/\sigma_x\sigma_y$

also adopted here.

Different than in the price series, Garch term (β) seems not to be a determinant for volatility (all $\beta's$ were not statistically significant). In other words, long run variance did not play a role in the explanation; just the volatility (α) in the previous period seemed to be relevant for returns' variance. Then, persistence of volatility in returns will be given just by the Arch term (α). Oil is still accounting for the largest persistence (0.36), but it is much less than the persistence found in the price series. Oil also had the largest long run variance in returns (8.13).

Dummies in volatilities were not significant (we tested also with just one of the two, but the results were similar), the only exception was the intercept dummy for 2008 (DI2008), which was relevant and with the expected sign (positive) for NAC returns, representing a positive impact on volatility.

Table 5: Results for CCC and DCC using Returns series

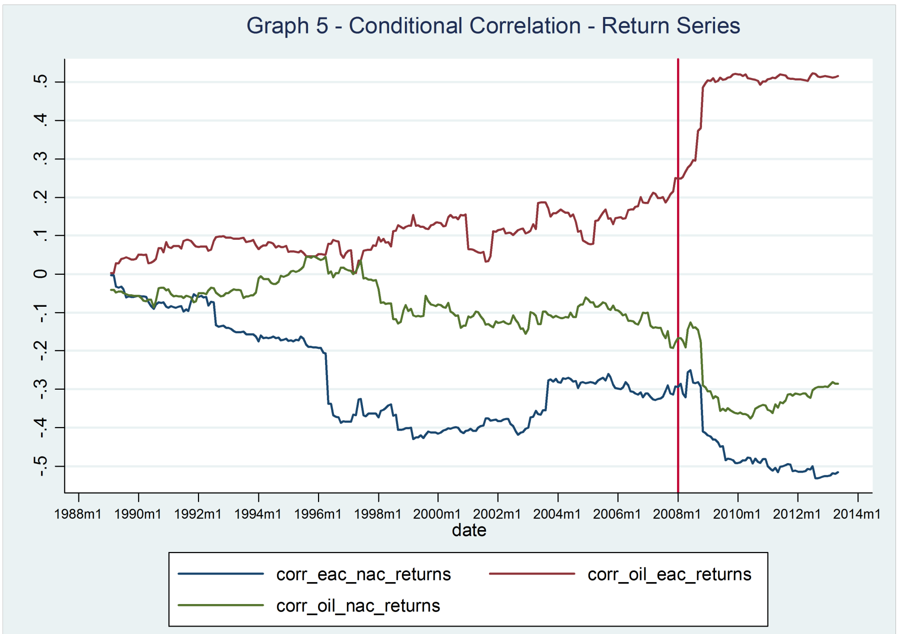
	CCC		DCC	
Variables	Coef.	Int. Conf.	Variables	Coef.
Oil				
_cons	1.631*	[0.290,2.973]	1.449*	[0.138,2.759]
ARCH_Oil				
Arch (α)	0.390***	[0.185,0.595]	0.384***	[0.180,0.589]
Garch (β)	-0.0498	[-0.211,0.112]	-0.106	[-0.376,0.163]
DI2002	0.106	[-0.398,0.610]	0.201	[-0.306,0.708]
DI2008	-0.601	[-1.231,0.0295]	-0.242	[-0.908,0.423]
_cons	4.801***	[4.446,5.157]	4.823***	[4.417,5.229]
EAC				
_cons	0.00789**	[0.00195,0.0138]	0.00567*	[0.0000461,0.0113]
ARCH_EAC				
Arch (α)	0.211***	[0.0863,0.336]	0.199**	[0.0756,0.323]
Garch (β)	0.248	[-0.0721,0.569]	0.0554	[-0.725,0.835]
DI2002	-0.575*	[-1.059,-0.0905]	-0.473	[-0.958,0.0121]
DI2008	0.0736	[-0.543,0.690]	0.516	[-0.0949,1.127]
_cons	0.00167***	[0.000764,0.00258]	0.00200***	[0.000904,0.00310]
NAC				
_cons	-0.108	[-0.300,0.0842]	-0.0909	[-0.283,0.101]
ARCH_NAC				
Arch (α)	0.167*	[0.00675,0.328]	0.161*	[0.00136,0.321]
Garch (β)	0.330	[-0.000850,0.660]	0.326	[-0.00963,0.663]
DI2002	-0.0127	[-0.529,0.503]	0.0411	[-0.472,0.554]
DI2008	0.903**	[0.321,1.485]	1.081***	[0.505,1.657]
_cons	0.243	[-0.375,0.861]	0.251	[-0.370,0.872]
Q.corr(Oil,EAC)	0.301***	[0.192,0.410]	2.037	[-0.909,4.983]
Q.corr(Oil,NAC)	-0.153**	[-0.266,-0.0394]	-1.266	[-3.393,0.861]
Q.corr(EAC,NAC)	-0.383***	[-0.482,-0.284]	-1.621	[-3.863,0.620]
Adjustment				
lambda1			0.0178	[-0.00123,0.0368]
lambda2			0.976***	[0.966,0.987]
N	292		292	
AIC	2518.8		2484.0	
BIC	2596.0		2568.5	

Source: Authors. Mean Equation: $Y = const$; Variance Equation:$H_t = w+\alpha.Arch+\beta.Garch+\epsilon$. Notes: a) 95% confidence intervals in brackets; b) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Regarding cross volatility (quasi-correlations parameters), their signs were positive between Oil and EAC in both models. Hence, increases in volatility of Oil likely will follow by positive spillovers in EAC. In the CCC estimations, these quasi-correlations' parameters were statistically significant, but the opposite occurred in the DCC model. According to Aielli (2013) and Engle (2009), there is no problem in the quasi-correlations to be larger than 1[20].

Unlikely the price series, the series of returns have not all series moving in the same direction. Quasi-correlations between Oil and NAC in both models (CCC and DCC) are negative. So returns of Oil and NAC are moving in opposite directions. Note that there is no problem in prices and returns showing different results, since it is entirely possible to have positive correlations in prices and negative correlations in returns for the same variables.

In order to verify if correlations between series are increasing over time, we have the Graph 5 with Corr (Oil, EAC), Corr (Oil, NAC) and Corr (EAC, NAC).



Source: Authors with results from DCC model. X = 2008m1 is a reference line for Financial Crisis

Graph 5 shows the anticipated results obtained from the estimations for quasi-correlations. Not surprinsingly, the relation between Oil and EAC returns is near zero, or weakly positive, in the first half of the sample, and it has a strong increase in recent periods. On the other hand, Oil and NAC returns have correlations near zero until 1998, after that reduced until values near -0.5 in recent periods.

Note that exactly in the peak of the Financial Crisis, last quarter of 2008, we have a break in the series, causing strong increase in Corr (Oil, EAC) and strong reduction in Corr (Oil, EAC).

6 Discussion and Implications

Our results have some implications for traders and policy makers. Agricultural commodities should not be treated as a homogenous group, especially regarding the transmission volatility and conditional covariance among returns. Considering a portfolio with oil bonds or bonds correlated with oil, diversification strategies should be revised. Energy Agricultural Commodities (EAC) (sugar, soybeans and corn) should have a minor proportion than Non-Energy Agricultural Commodities (NAC) (coffee, rice, cotton, sunflower and wheat).

These results are in line with the volatility transmission literature regarding the increasing volatility during Financial Crisis and Food Crisis and with increased conditional correlations between oil and agricultural markets. The results about differences in volatility transmission cannot be compared with other studies because we did not find similar research question in the empirical literature. In other words, there was no other study that used the idea of splitting agricultural markets into energy and non-energy commodities and then measuring volatility price transmission from oil to these markets.

[20]Output from Stata.12 was not re-scaled to ensure that matrix has proper correlation properties (Engle, 2009, p. 48).

The literature about agricultural commodity volatility often says that the reasons for its increase are: i) oil spillovers (Ji and Fan, 2012; Serra (2011); ii) financialization (Fleming et. al. 2005); iii) American monetary policy (Askari and Krichene, 2008; Nazlioglu et. al. 2012); iv) macroeconomic factors such as increases in demand for commodities from China (Gilbert, 2010); v) biofuels (Babcock, 2012; Ciaian and Kancs, 2011; Serra, 2011). Note that all factors pointed by the literature are macro factors, so attempts to minimize volatility are very limited[21].

In terms of reasons for large volatility in agricultural markets, note that if the argument of inelasticity in agricultural markets is valid to justify a high price volatility, biofuels should not be a reason for increasing volatility because they increased elasticity in these markets (fuels should be more elastic than food). Then, a natural conclusion that biofuels should reduce price volatility is correct. But it could be true if we were talking about a free market situation, and it is not the case for biofuels market.

In a free market situation the rise in sugar demand (for example) by biofuels would generate increases in prices and quantities to be produced, but there is nothing indicating that this would increase price volatility. The problem is that biofuels are often introduced by mandates (government says that a market share or a fixed quantity is ensured), and this introduction not just shifts demand, but also changes its slope, becoming more price inelastic. Summing up, biofuels could cause two different price volatility effects in agricultural markets: i) to reduce price volatility because of increase in price elasticity; ii) to raise price volatility because of integration with a more volatile market (oil). But, the nature of insertion (by mandates or fixed mandates) did not allow any kind of reduction in price volatility. This discussion drives us to the question on the possibility to introduce biofuels without having these collateral effects.

Flex-fuel cars could be an option in a sense of insertion more close to market conditions. The use of flex- fuel cars would be given some flexibility to mandates as suggested by Babcock (2011), the blending can change in each fuel supply, following markets conditions and being a kind of countercyclical mandate (increasing biofuels demand when oil is expensive and decreasing that when oil is cheap).

Serra and Gil (2012) have other two recommendations to mitigate volatility in agricultural markets: i) public stock management or public information about stocks - price transmission being smoothed; ii) promotion of development of second generation biofuels - reducing competition for crops and reducing volatility because of introduction of some elasticity in supply.

According to FAO-OCDE (2013), biofuels policies are in a turning point. Two of major sponsors by global biofuel demand, US and Europe, are revising their policies, and they are concerned with collateral effects as deforestation and global hunger, and also with supply capacity. If mandates are reviewed in the way that gives less importance to biofuels, it is likely that integration market will be reduced (being other "natural experiment" and a nice start point for new researches).

7 Conclusions

In this paper we tried to answer if there are volatility spillovers from oil market to agricultural commodities, and if there are differences in this transmission by type of agricultural commodities into two groups: i) agricultural commodities that are used in biofuels production (EAC) – corn, sugarcane and soybean; ii) agricultural commodities that are not used in biofuels productions – coffee, rice, cotton, sunflower and wheat.

The information about volatility spillovers were in the quasi-correlations of the estimated Mgarch model. Results showed that prices of the three indexes, Oil, EAC and NAC, move in the same direction. On the other hand, results for returns showed that conditional correlation between Oil and EAC is positive and negative for Oil and NAC. The graphs of predicted conditional correlations showed that correlations became stronger in recent periods with high peaks during Financial Crisis 2007-08. This result highlights that an old strategy of traders to invest in agricultural commodities bonds, trying to diversify their portfolios, could be a mistake. First, because there is high conditional covariance between oil and EAC returns, then this kind of agricultural commodity is not an option to diversify portfolios composed by oil bonds or other assets correlated with oil. Second, this covariance became high especially in those periods where diversification strategies are more important, such as times of crisis. For a better diversification, NAC bonds are likely a better option than EAC.

According to the research question addressed in this study, future research agenda can mainly pro-

[21] There are also localized issues that are likely to increase volatility, such as crop shortfalls. For this kind of problem, public countercyclical policies are usually used (Cepal, 2011).

ceed in two ways: i) other statistical approaches to measure volatility and its spillovers; ii) try to found other reasons for why agricultural commodities volatility increased. We supposed that DCC has a mean-reverting data generating process. So, in the search for other statistical approaches, such attempts should give more flexibility to the model to be tested if there are asymmetric dynamics. Other econometrical approaches to measure volatility spillovers are newly causality test proposed by Hafner and Herwartz (2008). They suppose shocks in volatility of one variable and to see what happens with the other one. Since the present study used monthly basis data, the re-estimation of the model using daily and weekly data can also be an interesting possibility.

Regarding the reasons on why volatility in agricultural markets is increasing, we tried to start this investigation supposing that biofuels have a role in this explanation. But, research considering other factors are necessary, mainly in a sense of accounting for all factors that are positive correlated all together (macro factors, financialization and American monetary policy, as example).

Most the attempts to reduce the price volatility are not feasible because the possible instruments are out of control (oil market, China's demand, and others). Alternatively, policy makers could try a different market insertion in biofuels case, which drives less volatility than the actual policies adopted. Policies that allow for a market self-adjustment, such as the use of flex fuel cars, for example.

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