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Abstract: This paper investigates the daily volatility spillovers between crude oil prices and a select group of agricultural staples. Empirical findings confirm that the price series under study exhibit nonlinear dependencies which are inconsistent with chaotic pattern. The Johansen-Juselius cointegration test rules out long-run equilibrium relationships between the crude oil prices and the commodities under study. The dynamic conditional correlations (DCC) suggest that the association between agricultural commodities and the crude oil varies over time. The spectral and cross spectral analyses confirm that volatilities in crude oil prices are associated with volatilities in the agricultural products in the sample. Bivariate EGARCH model and the Granger causality tests confirm this relationship.

Keywords: Crude oil prices; Volatility; EGARCH model; Spectral analysis; Cross spectral

JEL Classifications: G00, G15, G14

1. Introduction

As economies continue to urbanize and industrialize, their demand for oil increases significantly. For instance, Martenesn (2013) shows that between 2005 and 2011, China's GDP grew roughly 75%, while its oil consumption grew 36%. India for the same period showed a similar trend, its oil consumption grew at a rate of over 22%, as its GDP grew about 40% during that period. Martensen (2009), shows that for one percent growth in global GDP, oil consumption rises by twenty five basis points or roughly a four to one ratio.

Temporary and medium term frictions in the crude oil markets result in price volatilities in the for crude oil and its derivatives. While temporary periods of oversupply do happen, the long-run trends do not indicate oversupply in this market. Sadorsky (2004) discusses the effects of unexpected events that change supply and demand for oil and add to the risk in oil futures prices, thus, increasing risk premiums, which negatively impact equity prices.

A rich volume of research has been devoted to research on causality, cointegration, the short- and long-run relationships between crude oil price shocks, macroeconomic variables, as well as equity markets (see Leblanc and Chinn, (2004), Jones *et al.* (2004), Labonte (2004), Greenspan (2005), and Klein *et al*. (2005)).

Our paper is motivated by the following considerations. First, the volatility in oil prices during decades of 2000 and 2010 are expected to continue. Crude oil price volatility appears to spread to all sources of energy due to substitutability of various energy resources in production activities and consumption in the economy.

Second, the behavior of prices of various commodities may prove linear models including autoregressive vector methodologies, cointegration and vector error correction models, and Granger causality tests in a linear framework, are inappropriate tools of investigation in the presence of nolinearities in price and return series. Time series that are nonlinear in mean may be susceptible to nonzero higher order moments such as variance, skewness, and kurtosis. Various ARCH and GARCH models, analysis in the frequency domain, and nonlinear Granger causality tests may be better suited in these cases.

In this research, we examine the relationship between the crude oil prices and several important agricultural staples. Having determined that each price series in nonstationary, we test for the long-run equilibrium relationship between crude oil prices and each of the agricultural products. Johansen-Juselius test of cointegration rejects the null hypothesis of cointegration between each price pair. We proceed with deploying GARCH, bivariate VAR-EGARCH and spectral analysis to achieve our research objectives.

Our findings in the time series and frequency domains suggest that the crude oil price volatility is associated with volatility in agricultural commodities. Causality tests confirm these findings and lend robustness to these conculsions.

The remainder of the paper is organized as follows. Section 1 introduces the research. Related literature is covered in section 2. Section 3 discusses the data and methodology of the paper. Section 4 presents the empirical findings. Summary and conclusions are presented in Section 5.

2. Related Research

A significant body of past research investigates the relationship between crude oil price or retuns volatility and equities (see Sadorsky (1999), Faff and Brailsford (1999), Narayan and Narayan (2010), Zhu *et al*. (2011), Basher *et al*. (2012), among others). There are precious few papers addressing the same relationship for agricultural commodities. In the following, we briefly summarize those that examine commodities, currencies, and finally precious metals and methodologies that they employ.

Soytas *et al*. (2009) employ Toda–Yamamoto causality tests to investigate the information transition from world oil prices to interest rate, lira–US dollar exchange rate, and domestic spot gold and silver prices in Turkey. Sari *et al*. (2010) deploy Autoregressive distributed lag model, VAR and examine impulse responses to investigate co-movements and information transmission among the spot prices of four precious metals (gold, silver, platinum, and palladium), oil price, and the US dollar/euro exchange rate. They find evidence of a weak long-run equilibrium relationship but strong feedbacks in the short run. The spot precious metal markets respond significantly (but temporarily) to a shock in any of the prices of the other metal prices and the exchange rate. In conclusion, the results suggest that investors may diversify at least a portion of their portfolio risk away by investing in precious metals, oil, and the euro. Policy implications are provided.

The association of crude oil prices with food prices, and potentially inflationary pressures it imparts on the economy, justifie research on this subject. Our paper contributes to the literature by investigating the link between the crude oil return series (percentage change in price) and agricultural commodities in time series as well as the frequency domain. It, therefore, complements the findings of other papers which are mostly related to financial assets and in the time domain. To the best of our knowledge, this is the first paper that attempts to examine the subject in the frequency domain. A brief description of the methodology follows.

3. Data and Methodology

We study the daily agricultural commodities and crude oil prices for the period of March 1st, 2010, through July 6th, 2015, over thirteen hundred daily observations. Crude oil price are represented by the US crude West Texas Intermediate Cushing. Nearby futures contract prices of generic corn, soybean and wheat are from the Chicago Board of Trade. All data are taken from Bloomberg data base. Percentage changes in price levels (returns) are obtained by taking the ratio of natural logs of the prices as in $R_t = (\ln(P_t/P_{t-1}))\cdot 100$, where P_t represents the daily values.

Each price series is tested for stationarity on commonly known statistics. To test for nonlinearity and possible chaotic behavior, the Correlation Dimension of Grassberger and Procaccia (1983) and Takens (1984), and the BDS statistic of Brock, Dechert, and Scheinkman (1987) are applied (see Adrangi *et al.* (2001a), Adrangi *et al.* (2001b), and Adrangi *et al.* (2004)). These tests are portmanteau tests of linearity vs. possible nonlinearities of undetermined origin, including low dimensional chaos. While all price series demonstrate nonlinearities, these nonlinearities are not consistent with chaotic patterns.

As shown in the literature (Box and Jenkins (1976), Chatfield (1989)), the behavior of most variables maybe examined both in time or frequency domains. In this paper, we deploy both types of analyses using GARCH models in the time domain, and spectral /co-spectral analyses in the frequency domain. Examining retunrs in the frequency domain complements the anyalysis in the time domain, especially considering that nonlinearities often complicate econometric modeling.

The spectral analysis is based on expressing a stationary times series in terms sine and cosine waves of various frequencies. To estimate the amplitude of the sinusoidal components of a time series, periodograms (sample spectral density function) are defined. The sample spectrum is the Fourier cosine transformation of the estimation of the sample autocovariance function, and is written as follows:

$$I(f) = 2\{\sigma_0 + 2\sum_{F=1}^{N-1} \sigma_F \cos 2\pi f F\}, \quad 0 \le f \le 1/2 \qquad (1)$$

The sample power spectrum is analogous to the probability density function in the continuous domain or a histogram in discrete domain. Converting variance and autocovariances to auotcorrelation coefficients, we obtain the following smooth estimate of the spectrum, *I(f)*.

$$\hat{P}(f) = 2\{1 + 2\sum_{F=1}^{N-1} \lambda_F \rho_F \cos 2\pi f F\}, \quad 0 \le f \le 1/2.$$

The variables λ_F are known as "lag window." In the estimation process, one increases "the bandwidth" of the estimate to derive smooth estimates of the spectrum. We will estimate the individual spectrums for various time series utilizing three differently defined lag windows, i.e., Bartlett, Tukey, and Parzen.

The standardized spectrum may be written as

$$\hat{P}(\theta_j) = 2\{1 + 2\sum_{F=1}^{N-1} \lambda_F \rho_F \cos 2F\theta_j\} \tag{2}$$

where $\theta_j = j\pi/m$ and $j = 0, 1, 2, \ldots, m$, and m is the window size, and ρ_F is the autocorrelation coefficient of order F.

Examining co-spectral densities may shed further light on the association between two time series in the frequency domain. However, cross-spectral density is often complex-valued and is not directly informative. In our analysis we focus on the "phase lead" and "coherence squared." The phase lead measures the fraction of cycle that one series leads the other or lags behind in each frequency. The coherence squared measures the fraction of the variance of a time series which is explained by the variance in other series, in each frequency.

Koutmos (1999), Adrangi *et al*. (2015), among others, provide evidence that the volatility transmission among various assets and commodities may follow an asymmetric process. To account for asymmetric shock response within and across markets, we estimate bivariate EGARCH models.

The bivariate EGARCH model is given as follows.

$$R_{it} = \alpha_{i,0} + \sum_{j=1}^{2} \alpha_{ij} R_{i,t-1} + \varepsilon_{i,t} \qquad (i, j = 1,2) \tag{3}$$

$$Ln(\sigma_{i,t}^2) = \beta_{i,0} + \sum_{j=1}^{2} \beta_{ij} \varphi_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2) \qquad (i, j = 1,2) \tag{4}$$

$$\varphi_j(z_{j,t-1}) = (\,|z_{j,t-1}| - E(|z_{j,t-1}|) + \delta_j z_{j,t-1}) \qquad (i, j = 1,2) \tag{5}$$

where $z_{j,t} = (|u_{j,t}/\sigma_{j,t}| - \sqrt{2/\pi}) + \delta_j u_{jt}/\sigma_{j,t}$

and

$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t} \qquad (i, j = 1,2) \tag{6}$$

R_{it} is the percentage daily returns in market i and at time t; $\sigma^2_{i,t}$, and $\sigma_{i,j,t}$ are the conditional variance and covariances in market i, and between markets i and j, at time t, respectively; ρ_{ij}, the conditional correlation coefficient between markets i and j; $z_{i,t} = \varepsilon_{it}/\sigma^2_{i,t}$, is the standardized innovations of market i at time t.

The coefficients of the model in equaitons (3)-(6) are estimated by maximizing the likelihood function using a combination of the simplex method and Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm.

To examine the possibility of dynamic correlation between crude oil and other commodity markets, we estimate and present the graphs of the dynamic conditional correlation (DCC) derived from the GARCH model given by $\rho_{ij}(t) = M_{ij}(t)/\sqrt{M_{ii}(t)M_{jj}(t)}$, where M represents modified diagonal covariance matrix from the GARCH models.

4. Empirical Findings

4.1 Stationarity and chaos tests

Examining crude oil and other commodity prices graphically, suggests that prices show mean and covariance nonstationarity. On the contrary, returns of all commodities are clearly mean-stationary, however, may be covariance non-stationary. The graphic evidence (not presented for the purpose of brevity) of nonstationarity calls for formal statistical tests and possibility of nonlinearities in the series. We provide the statistical evidence of the behavior of these series in Table 1.

Table 1 presents the summary statistics of prices and the diagnostics for the R_t series. The returns series are found to be stationary employing the Augmented Dickey Fuller (ADF), Phillips-Perron and KPPS statistics. There are linear and nonlinear dependencies as indicated by the Q and Q^2 statistics, and Autoregressive Conditional Heteroskedasticity (ARCH) effects are suggested by the ARCH (6) chi-square statistic. Our findings from Table 1 maybe summarized as follows: (i) there are clear indications that nonlinear dynamics are generating the daily prices, (ii) these nonlinearities may be due to ARCH effects, and (iii) whether these dynamics are chaotic in origin is the question that we turn to next. The correlation dimension and BDS statistics are employed to see if the nonlinearities are consistent with chaos.

The Correlation Dimension (SC^M) estimates for asset returns filtered by AR(1) and GARC(1,1) models suggest that the series under consideration are not showing signs that are consistent with low dimensional chaos. According to the BDS statistics the null of no nonlinearity in the [AR(1)] errors is rejected for all of the return series. However, the BDS statistics for standardized residuals from the GARCH(1,1) models are mostly insignificant at the 1 and 5 percent significance levels. The BDS tests support the results of correlation dimension, but are not presented in the paper. These findings are not reported for the purpose of brevity.

4.2 Spectral and Co-spectral analysis

Examining the standardized spectral densities for the agricultural products presented in Figure 1 with four panels, shows that the majority of the returns variations of corn are concentrated in medium frequencies. This pattern of variation in returns may be a sign of seasonalities in the corn market. For instance price variations would be higher during the harvest season which tends to be some time from October through Novemeber in the US and Europe, and October through November in China. Similarly, the soybean and wheat prices demonstrate much more variations in the low and medium frequencies than the higher frequencies. One may conclude that the agricultural commodities under study are prone to less volatility on the daily or monthly basis than on seasonal and cyclical trend bases.

The spectral density for the crude oil, unlike those of agricultural commodities exhibits high frequency in variations of the crude oil prices, thus, much higher volatility in short-term or daily basis than the commodities under study. Short-term high volatility of crude oil prices may be expected as energy prices tend to be volatile. Many central banks compute a core inflation index which excludes both energy and food prices because they tend to be highly volatile.

While crude oil retunrs show high variation at high frequency, retunrs of agricultural commodities vary over medium and higher frequencies, there may still be some components of both series in the frequency domain that are coherent, i.e., move in tandem. To investigate this possibility, we analyze co-spectral density functions between the crude oil and each commodity. The cross-spectrum indicates how much linear information is transferred from one signal to the other (and vice-versa), i.e., the "burden" of the line transfer at each frequency. We will focus on “Coherence,” and “phase” between two series or their representations in the frequency domain.

Table 1. Diagnostics and summary (Interval: 03/2010-07/2015; N=1345)

Returns are given by R_t=100*ln(P_t/P_{t-1}), where P_t represents closing spot or nearby contract prices on day *t*. ADF represents the Augmented Dickey Fuller tests (Dickey and Fuller (1981)). The LM-ARCH(6) statistic is the Engle (1982) test for ARCH (of order 6) in residuals of a random walk model and is χ^2 distributed with 6 degrees of freedom.

Panel A: Price levels

Tests	Crude oil	CORN	SOYBEAN	WHEAT
ADF_trend	-1.103	-1.571	-1.880	-2.427
PP_trend	-1.064	-1.545	-1.817	-2.425
KPPs_trend	0.685	1.426	0.785	0.879
Q(36)	38748.000 ^{a}	42435.000^{a}	39462.000^{a}	35572.000 ^{a}
Q^2(36)	37569.000	41499.000 ^{a}	38814.000^{a}	35386.000 ^{a}
LM-ARCH (6)	57.769 ^{a}	18.190 ^{a}	17.732 ^{a}	73.882 ^{a}

Panel B: Percentage changes

Tests	Crude oil	CORN	SOYBEAN	WHEAT
ADF_trend	-37.755^{a}	-35.738^{a}	-36.263^{a}	-35.842^{a}
PP_trend	-37.775^{a}	-35.729^{a}	-36.276^{a}	-35.836^{a}
KPPS_trend	0.261^{a}	0.266^{a}	0.263^{a}	0.115^{a}
Q(36)	32.393	75.951^{a}	50.9b2^{b}	53.884^{b}
Q^2(36)	144.670^{a}	7.742	126.270^{a}	473.841^{a}
LM_ARCH (6)	57.212 ^{a}	2.081	17.644^{a}	73.979^{a}

Panel C: Summary descriptive statistics for model variables. All variables are in level.

Statistics	Crude oil	CORN	SOYBEAN	WHEAT
Mean	88.711	547.187	1276.205	653.282
Stand Dev	15.258	146.941	207.706	111.966
Skewness	-1.155	0.057	-0.163	0.217
Kurtosis	3.798	1.529	2.106	2.493
J-B	335.937^{a}	122.374^{a}	50.945^{a}	24.996

Panel D: Bilateral Johansen-Juselius cointegration test, crude oil prices and commodities

Tests / ***r***	**CORN**		**SOYBEAN**		**WHEAT**	
	λ_m	λ_t	λ_t	λ_m	λ_t	λ_m
H0: r = 0	33.76	22.77	8.33	8.23	13.76	9.17
H0: r < 1	10.99	10.58	0.09	0.09	4.59	4.59

Notes: (1) Order of lags in VAR models is 1, determined by the AIC, SBC, likelihood ratio test (LR) and adjusted likelihood ratio test ALR.

(2) Cointegration with unrestricted intercepts and no trends in the cointegrating VARs.

(3) P-values from MacKinnon-Haug-Michelis (1999) for both λ_m and λ_t are consistently larger than 20%, establishing no statistical support for a long-run equilibrium relationship between crude oil price with the commodities under study.

(4) Crude, is daily spot prices for West Texas Cushing crude oil, CORN, SOYBEAN, and WHEAT are daily prices of nearby generic commodities futures contracts at the CBOT. All data are taken from Bloomberg data base.

(5) Q(36) and Q^2(36) are the Ljung Box statistics for prices and their squared values.

(6) ^{a}, ^{b}, and ^{c}, represent statistical significance at 0.01, 0.05, and 0.10, respectively.

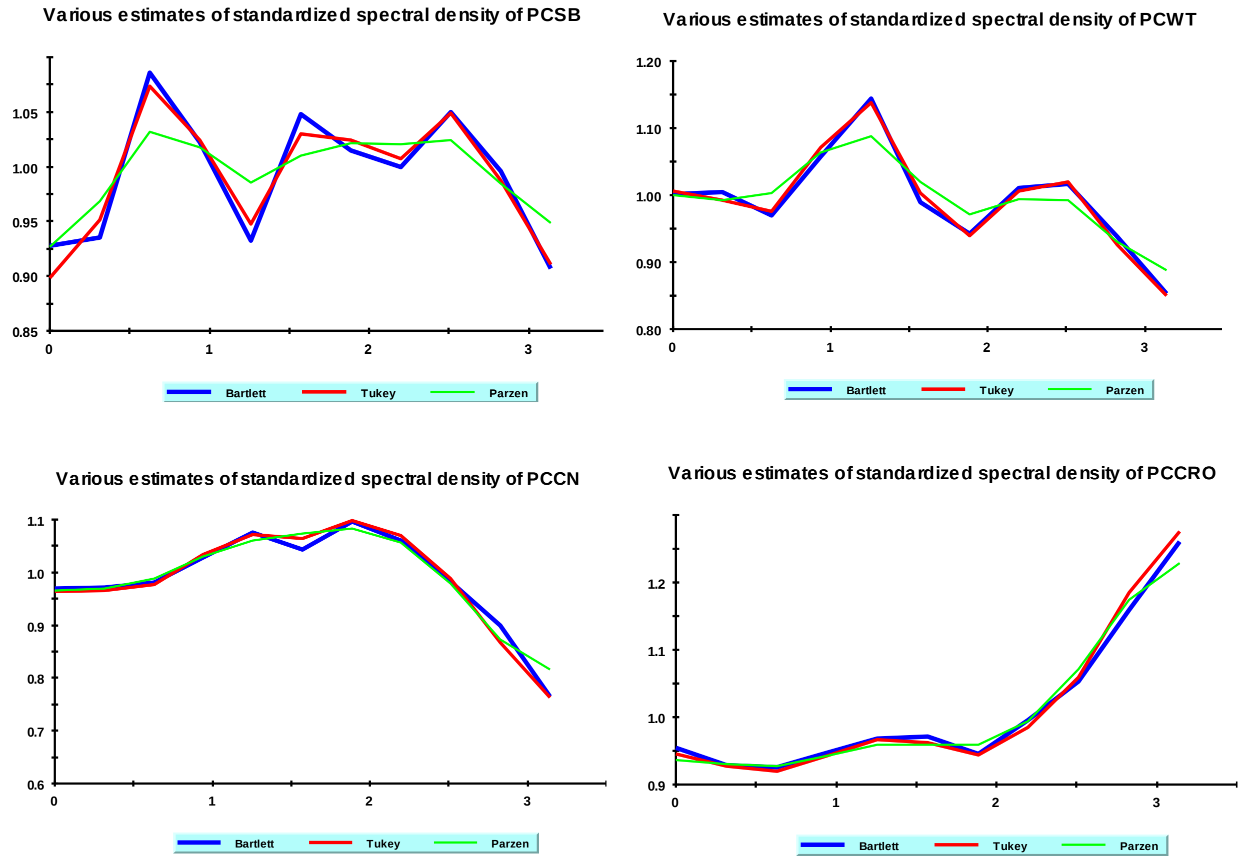


Figure 1. Standardized spectral densities

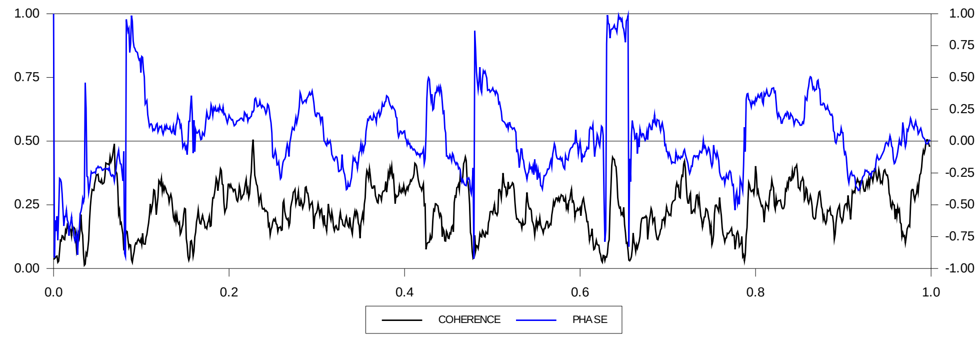
Notes: CRO, CN, SB, WT stand for West Texas Intermediate Cushin crude oil spot prices, and corn, soybean, and wehat nearby furtures prices. The prefix PC, indicates percentage change in each price, i.e., daily reutns on these commodities.

Coherence is a measure of the degree of relationship, as a function of frequency, between two time series. It describes the correlation (or predictable relationship) between waves at different frequencies or moments in time. Alternatively, the coherence indicates how much linear information of one signal is explained by the other signal. The coherence of a linear system of relationship reveals the fraction in the volatility of movements in variable y that is due to the variable x at a frequency. It may be used to estimate the causality between the two signals.

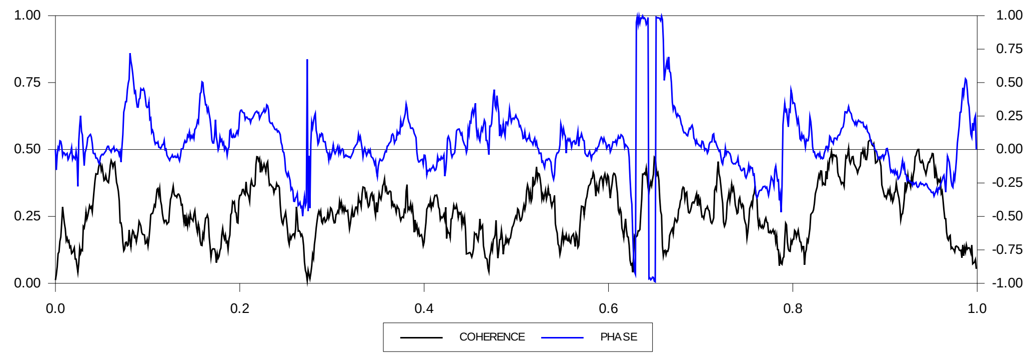
If the coherence (C_{xy}) is between zero and one, it could be an indication of the presence of random distrubances, which are common in markets. Alternatively, it could be showing that the assumed function relating $x(t)$ and $y(t)$ is not linear. Another possibility may be that $y(t)$ is dependent on $x(t)$ as well as other inputs. If the coherence is equal to zero, it is an indication that $x(t)$ and $y(t)$ are perfectly unrelated. For instance, the coherence may be viewed as the relationship between the ground water and tidal movements of the ocean water levels. It has been shown that the well water levels follow the rising ocean tide.

Figure 2 in three panels presents the phase lead and coherence beween the crude oil price and each commodity price series. Based on the lead phase curve, crude oil returns lead wheat in a high percentage of cycles. For instance in the 0-0.2 frequency, up to roughly fifty percent of the cycle, crude oil prices lead the wheat price. In almost all frequencies and for all three commodities this observation seems to hold true consistently. In some frequencies and for some of the agricultural commodities, the fraction of cycle is even higher than fifty percent.

(a) Crude oil and Corn



(b) Crude oil and Soybean



(c) Crude oil and Wheat

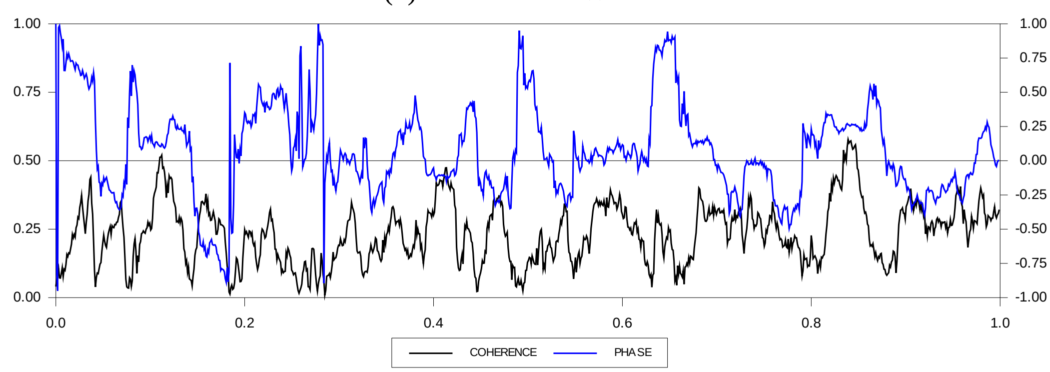


Figure 2. Cross-spectral phase lead and coherence graphs

Turning to the graph of coherence, one concludes that at all frequencies (low to high) a high percentage of variation in the returns of the three commodities appear to be explained by the variance in the crude oil eturns. These observations strongly support the hypothesis that the crude oil price changes lead the price variations in the markets for the agricultural commodities in this sample. The findings of the phase lead and coherence squared also suggest that information arrival occurs in crude oil markets first, and crude oil markets inform the commodities market. It is important to note that returns variations in the high frequency may represent short-term price volatilities, while those variations in medium frequencies may correspond with the medium-term cyclical variations. Low frequency changes in returns resemble long term trend in time series presentation of the price variables. In this context, the coherence between the commodity and crude oil returns point at a correlation or even a causality between the crude oil and the returns of the agricultural commodities in this sample at all frequencies, or short-term, medium-term, and in the long-term in the time domain.

Given that mathematically spectral analysis is equivalent to the results of the covariance in the time domain, and the spectral density function serves the same purpose as histograms in the time domain, we use the information gleaned from the spectral and the cross spectral investigation and estimate bivariate-EGARCH models. These models ascertain the information arrival and return volatility spillovers in an asymmetric fashion that the coherence and phase graphs suggest. Furthermore, to complete the analysis, we deploy the nonlinear Granger causality tests to establish the possible causal relationship rigorously.

Table 2. Bivariate asymmetric VAR- EGARCH model with volatility spillovers

Crude oil price and commodities

Mean Equation	**Crude**	**Corn**	**Crude**	**Soybean**	**Crude**	**Wheat**
Intercept α_{10}, α_{20}	-0.0049 (0.0511)	0.0243 (0.0574)	-0.043 (0.032)	-0.009 (0.011)	-0.031 (0.025)	-0.014 (0.017)
Own Lagged Return α_{11} α_{21}	0.0310 (0.1036)	0.2789 [a] (0.1089)	-0.161 [a] (0.032)	-0.008 (0.011)	-0.028 (0.025)	-0.008 (0.017)
Cross Lagged α_{12}, α_{22}	0.1321 [a] (0.0603)	-0.0437 (0.0652)	-0.063 (0.032)	-0.023 (0.011)	0.019 (0.025)	0.019 (0.017)

Variance Equation	**Crude**	**Corn**	**Crude**	**Soybean**	**Crude**	**Wheat**
Intercept β_{10}, β_{20}	0.0513 [c] (0.0309)	0.1899 [b] (0.0805)	0.038 (0.021)	0.002 [a] (0.0009)	0.028 (0.013)	0.025 [a] (0.009)
Lagged z β_{11}, β_{21}	0.0002 (0.0003)	-0.0001 (0.0004)	0.152 [a] (0.032)	-0.046 (0.011)	0.120 [a] (0.025)	0.021 (0.017)
Lagged z β_{12}, β_{22}	0.0854 (0.0756)	0.2501 [a] (0.0813)	0.009 (0.032)	0.017 (0.011)	0.011 (0.025)	0.218 [a] (0.017)
Lagged Conditional Variance γ_1 γ_2	0.9526 [a] (0.0247)	0.8577 [a] (0.0577)	0.964 [a] (0.017)	0.987 [a] (0.004)	0.974 [a] (0.032)	0.912 [a] (0.034)
Lagged stand. Shock δ_1 δ_2	-0.7293 [a] (1.2108)	-0.5711 [b] (0.2633)	-0.447 [a] (0.055)	-0.199 [a] (0.096)	-0.646 [a] (0.188)	-0.269 [a] (0.113)
Leverage Effect $\lvert -1+\delta_j \rvert/(1+\delta_j)$	6.3882	3.6630	2.616	1.497	3.620	1.736
Correlation	0.1471 [a] (0.0569)		0.285 [a] (0.027)		0.263 [a] (0.027)	

Diagnostics on Standardized residuals

Tests	**Crude**	**Corn**	**Crude**	**Soybean**	**Crude**	**Wheat**
Q(12), ε_t/σ	12.9307	21.0235	3.235	10.588	3.479	4.505
Q^2(12), ε_t/σ	8.4767	8.3158	8.722	10.630	10.183	7.699
$E(\varepsilon_t/\sigma)$	0.0117	-0.0248	0.016	0.009	0.007	0.004
$E(\varepsilon_t/\sigma)^2$	0.9748	0.9972	0.995	1.010	0.995	0.997
System Log Likelihood	-1024.7080		-3159.8907		-3158.306	

Notes: Q and Q^2 are the Ljung-Box statistics of standardized model residuals.
[a], [b], and [c], represent significance at 0.01, 0.05, and 0.10, respectively.

4.3 Bivariate EGARCH Model

Based on the findings reported in previous tables and graphs for returns, we propose and estimate VAR models in a bivariate GARCH context. VARs are appropriate for our modeling because Zellner and Palm (1974) and Zellner (1979) show that a VAR may be viewed as Taylor series approximation for nonlinear models and represents a flexible approximation to any wide range of simultaneous structural models. The statistics in Table 1 support the claim that GARCH models may explain the dynamic relationships between crude oil and agicultural commodities (see Engle (1982), Hsieh (1989)).

Table 2 reports the estimation results of the VAR-EGARCH model of equations (3)-(6) for bivariate crude oil price and other commodities under study. For all bivariate models δ_1 and $\delta_2 < 0$ along with positive β_{12} and β_{21}, verify that volatility transmission across markets is asymmetric. Statistically significant $\delta_j < 0$ confirms the presence of asymmetric volatility effects in each market, whereby negative shocks in each market lead to higher volatility than positive innovations.

The size effect (the degree of asymmetry) as measured by $|-1+\delta_j|/(1+\delta_j)$, are in the range of 2.616 to 6.3882 in the crude oil market, indicating that asymmetric shock effects in crude oil markets are significantly higher than other commodity markets, except corn. The agricultural commodites are far less sensitive to positive (innovations) and negative news. The unconditional volatility in all cases are finite as indicated by γ_1 and $\gamma_2 < 1$.

The conditional correlation coefficients between the crude oil prices and the agricultural commodities, given by equation (8) is the lowest at 0.1471 for corn and the highest for wheat at 0.2616. This coefficient is hovering around 0.20 for all markets except corn. In all cases, the time varying correlation coefficients are statistically significant but also significantly lower than unconditional correlation coefficients. This finding is consistent with our econometric expectations and those of other researchers (see Koutmos (1996), say) who show that accounting for the conditional heteroscedasticity could result in more accurate and usually lower pairwise correlation coefficients among asset returns. However, these correlation coefficients are expected to change over time as indicted before. The dynamic conditional correlations (DCC) are plotted in Figure 3 by three panels. DCC values are influenced by the time varying heteroscedastricity in the underlying price series. In every case, DCCs between crude and other asset prices demonstrates wide fluctuations over time. This shows that the relationships between these prices are time-varying and possibly asymmetric with respect to positive and negative news in the crude oil market. We perceive these observation as further support for the underlying nonlinearities stemming from volatility and need for GARCH type modeling.

Overall, statistical findings reported in Table 2 confirm that an EGARCH model, which accommodates the asymmetric shock transmission, is the appropriate model for our purposes. To compute the asymmetric effects of shock transmission, we compute $(-1+\delta_j)*(\beta_{ij})$ and $(1+\delta_j)*(\beta_{ij})$ for negative and positive shocks, respectively. In all cases, negative shocks to the crude oil prices of the past period, have a much larger percentage impact on the conditional volatility in crude and agricultural commodity markets, in comparison to positive shock of similar magnitude. The corn market exhibits the largest reaction in conditional volatility to positive and negative shocks to the crude oil prices with magnitudes of 0.0749 and 0.2766, respectively. Wheat and soybean markets are less sensitive to both types of shocks in the crude oil market. To summarize, the volatility reaction in all markets to own past negative innovations and crude oil price market negative innovations is much larger for all commodities. The average percentage impact on conditional volatility of all markets to negative shocks in the previous crude oil prices is roughly three times as large as the positive shocks. Our findings in this regard corroborate the conclusions by Koutmos (1996).

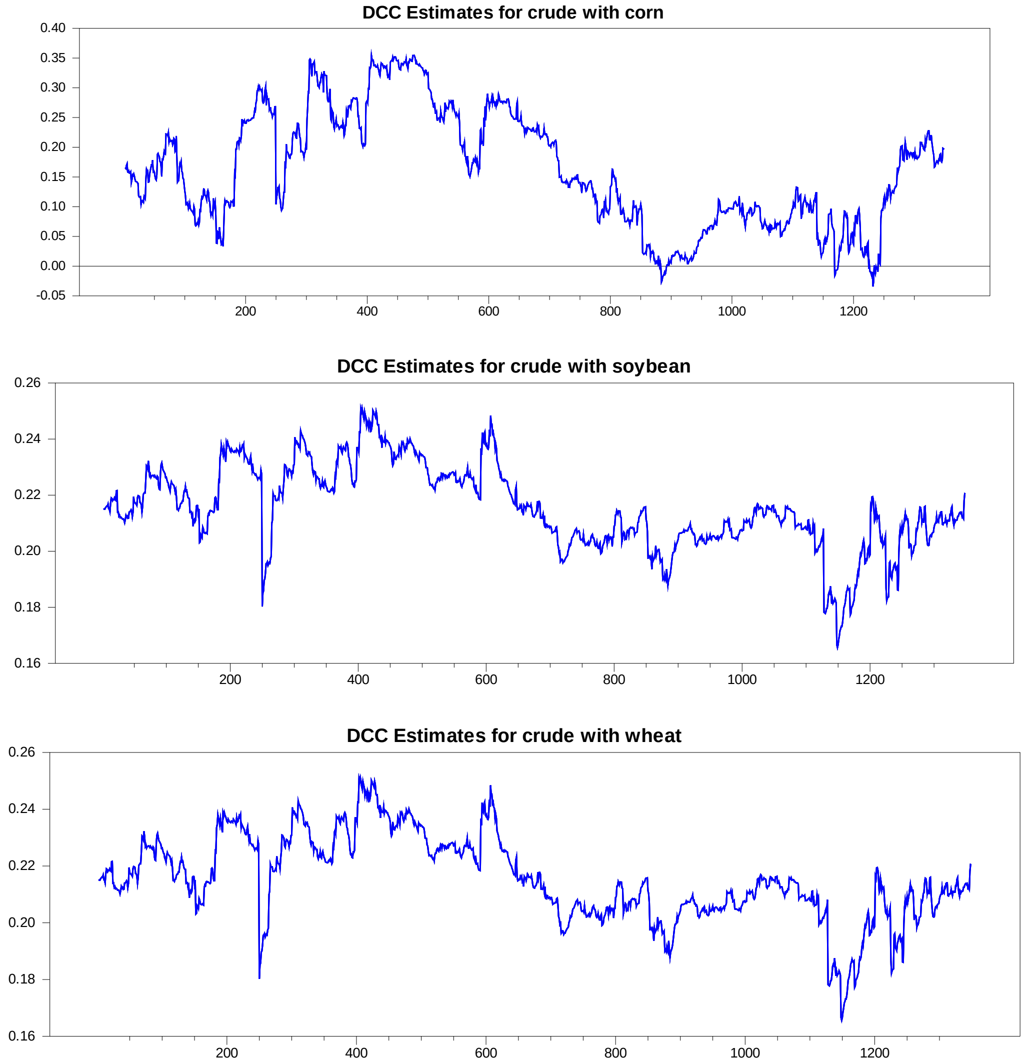


Figure 3. Dynamic Conditional Correlations between crude oil returns and commodity returns

4.4 Volatility spillover and non-linear Granger causality

The empirical findings thus far have shown that there is dynamic correlation between crude prices and other commodity markets. Furthermore, we have shown volatility spillover from crude oil markets into markets of these commodities. It may be useful to examine the dynamic relationship between crude oil markets and other markets that may be evidence of causality. We deploy a nonlinear extension of the standard Granger causality tests which test for a causal relationship between two variables in a linear and autoregressive framework (Granger (1969), and Geweke (1984)).

The nonlinear version of the test requires a smooth transition regression (STAR) such:

$$y_t = \pi_{10} + \pi_1^{'} w_1 + (\pi_{20} + \pi_2 w_t) F(y_{t-d}) + \delta_1^{'} v_t + (\delta_{20} + \delta_2' u_1) G(x_{t-e}) + u_t \qquad (7)$$

where $\delta_j = (\delta_{j1}, \ldots, \delta_{jq})'$, j=1, 2, $v_t = (x_{t-1},\ldots, x_{t-q})'$ and $G(\cdot)$ is a transition function. The following approximation to equation (7) is the basis for the test,

$$y_t = \bar{\pi}_{10} + \bar{\pi}_1{}' w_1 + (\pi_{20} + \pi_2 w_t) F(y_{t-d}) + k' v_t + \sum_{i=1}^{q} \sum_{j=1}^{q} \phi_{ij} x_{t-1} x_{t-j} + \sum_{i=1}^{q} \psi_i x^3{}_{t-1} + u_t, \tag{8}$$

where $k' = (k_1,\ldots,k_q)$, and non causality is supported by k_i=0, φ_{ij}=0 and ψ_i = 0; i = 1,…,q; j = 1,…, q. Under H0, the resulting test statistic has an asymptotic F-distribution with (q*(q+1)/2) +2q degrees of freedom.

Table 3 summarizes the results of the nonlinear Granger Causality tests for lags q = 5,…., 10 lags (see Skalin Tera è Svirta, 1999). The reported P-values for the F statistic in Table 3 test the joint null hypotheses of no causality, i.e., that k_i=0, φ_{ij}=0, and ψ_i=0. For all commodities and for all lag orders, the P-values are equal to zero or in some case around ten percent, showing that the H0 is mostly rejected and there is evidence of causality from the crude oil prices to all commodities in the sample. These findings support the findings of the spectral analysis and confirm that crude oil prices lead the price movements in agricultural commodities. The feedback is almost noexistent except in one case at the ten percent level.

Table 3. Nonlinear Granger causality test: P-values of the F-statistic for H0 of no nonlinear Granger Causality

Lags	Causing Variable	Caused Variables		
	Crude Oil Price	Corn	Soybean	Wheat
5		0.1204	0.0319	0.1038
6		0.3004	0.0496	0.2864
7		0.0595	0.0723	0.0284
8		0.0527	0.0796	0.0076
9		0.1045	0.0878	0.0023
10		0.0543	0.0895	0.0000
Lags	**Caused Variable**	**Causing Variables**		
	Crude Oil Price	Corn	Soybean	Wheat
5		0.4133	0.9667	0.3081
6		0.4181	0.8067	0.4704
7		0.2661	0.7394	0.4394
8		0.0729	0.6535	0.4017
9		0.1521	0.7794	0.6600
10		0.3514	0.7139	0.7146

Notes: In the top panel many F-statistics are significant at the usual levels with P-values less than 0.10. The bootom panel suggests that there is no feedback from agricultural commodities to crude oil prices.

Degrees of freedom are 25, 32, 42, 52, 63, and 75 for lags q=5 through 10, respectively.

5. Summary and Conclusions

This research analyzes the price volatility association between crude oil prices and three major agricultural commodities. Our initial tests show that all prices series are nonstatinary, and their returns exhibit nonlinearities and nonlinear dependencies that are inconsistent with low dimensional chaotic structure.

The graph of coherence leads us to conclude that a high percentage of variation in the prices of the three commodities appear to be explained by the variations of the crude oil prices in all frequencies (low to high). These observations strongly support the hypothesis that the crude oil price changes lead the price variations in the markets for the agricultural commodities in this sample and may confirm correlation or causality between the crude oil prices and the prices of the agricultural commodities in the short-term, medium-term, and in the long-term in the time domain.

Given that mathematically spectral analysis is equivalent to the results of the covariance in the time domain, and the spectral density function serves the same purpose as histograms in the time domain, we use the information gleaned from the spectral and the cross spectral investigation and estimate bivariate-EGARCH models. The results from estimated VAR-EGARCH models show that shock transmissions are asymmetric such that positive and negative shocks of the same size have unequal effects on the volatility of the other markets. We find that return volatility spillovers are much more pronounced following negative news in each market. This finding suggests that the negative news in crude oil markets may lead to elevated uncertainty in the other markets under study. Finding empirical evidence that indicate dynamic market interactions and information ransmission, we deploy the nonlinear version of the Granger causality test based on smooth transition regression (STAR). The empirical findings show that crude oil prices Granger cause the agriculatural products studied here, but there is no feedback. The nonlinear causality test results are robust for most lag structures considered.

The main findings of the study are as follows. First, the US agricultural commodity market price volatility is associated with crude oil price volatility. The negative news in crude oil market imparts significant degree of price volatility in agricultural commodities future markets. This could potentially lead to higher world food prices. Granger causality tests emphasize the importance of the crude oil markets in the basic staples markets and food prices. The policy ramification of these findings is that the US and major world economies should adopt long-term strategies and reserves to reduce market risks stemming from volatility in crude oil markets. Our results indicate that these strategies may bolster stability in other markets, including staples. These findings corroborate the findings of other research in the financial markets, among others.

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