Economics Bulletin

Volume 37, Issue 2

Short- and long-run causality across the implied volatility of crude oil and agricultural commodities

Elie Bouri
Holy Spirit University of Kaslik, Lebanon

Imad Kachacha
Holy Spirit University of Kaslik, Lebanon

Donald Lien
University of Texas at San Antonio, USA

David Roubaud
Montpellier Business School, France

Abstract

Unlike prior studies which often use realized variance or return series within a GRACH framework to examine time-domain linkages, this study employs CBOE implied volatility data from July 27, 2012 to September 30, 2016 within the frequency-domain causality framework in order to uncover short-, medium-, and long-run causal relations across crude oil, wheat and corn markets. Overall, the results show that the volatility causal relation differs between high and low frequencies. Specifically, we provide evidence in further support of the argument that the crude oil market dominates the corn market. The results also indicate that structural breaks characterize the causal relation between the implied volatilities of corn and wheat, which is found to differ between the short- and long-run. Implications for the analysis of hedging and risk management are discussed.

Citation: Elie Bouri and Imad Kachacha and Donald Lien and David Roubaud, (2017) "Short- and long-run causality across the implied volatility of crude oil and agricultural commodities", *Economics Bulletin*, Volume 37, Issue 2, pages 1077-1088
Contact: Elie Bouri - eliebouri@usek.edu.lb, Imad Kachacha - imadkachacha@usek.edu.lb, Donald Lien - Don.Lien@utsa.edu, David Roubaud - d.roubaud@Montpellier-BS.com.
Submitted: February 04, 2017. **Published:** May 14, 2017.

1. Introduction

Motivated by the simultaneous movements of both energy and agricultural commodities in similar directions, especially with the expansion of biofuel production, numerous studies have newly emerged attempting to study the interactions between these commodity markets (see, among others, Du et al., 2011; Nicola et al., 2016). Usually, existing studies have relied on price return and to a lesser extent on price volatility in studying inter-market linkages. In particular, return volatility has been typically measured as realized variance or modelled within a GARCH framework (e.g. Mensi et al., 2014b) although implied volatility is most often found to have more informational content and predictive power about future volatility (Jiang and Tian, 2005). Recently proposed by the Chicago Board Options Exchange (CBOE), implied volatility is backed out from option prices and thus reflects the market's expectation of volatility with an horizon corresponding to the maturity of the option.

Notably, potential differences in the volatility causal investigation between high and low frequencies represent an important issue and a concern for market participants who often use short- and/or long-term horizons in their trading strategies but are poorly informed about the dynamic of the volatility causality in the frequency-domain within the energy-agricultural commodity nexus. The presence of structural breaks represents another important issue that has to be addressed when examining the volatility causality across commodity markets. To address the needs of market participants and the related gap in the existing literature, we aim to uncover the short-, medium-, and long-run causal linkages across the implied volatility indices of crude oil, corn, and wheat while accounting for the presence of structural breaks.

This study differs from the existing literature in several ways and presents at least three important contributions. First, it uses implied volatility indices that reflect anticipative supplementary information that a model-based historical volatility could not (Jiang and Tian, 2005). Second, it employs the frequency-domain approach of Breitung and Candelon (2006) which provides innovations in modelling the causal relation among energy and agricultural commodity markets by uncovering short-run and long-run causality which should be of interest to economic actors who can tailor a trading strategy and risk management structures that are dependent not upon the usual time-domain but upon the frequency-domain. The latter approach decomposes the causality at different frequencies, and allows the causality at low frequencies to differ from that at high frequencies. This notable frequency domain approach, which provides broader and informative outcomes than in the standard Granger causality, has been very useful in modelling the relationships between financial variables (Grandojevic and Dobardzic, 2013; Gupta et al. 2015). Third, it accounts for the presence of structural breaks in the causal relation, otherwise the analyses could lead to distorted results and inferences.

2. Prior studies

The link between energy and agricultural commodity markets has been the subject of numerous studies. Baffes (2007) uses regression analyses to examine the effect of crude oil prices on the prices of 35 internationally traded primary commodities from 1960 to 2005. The author finds, among others, that agriculture commodities exhibit a strong response to crude oil prices. Mensi et al. (2014b) use a multivariate GARCH model and report evidence of significant return and volatility linkages between energy and cereal commodities. The authors also account for the impact of OPEC news announcements. Using a bivariate-VAR model to asses assess the co-movements between crude oil and food prices, Lucotte (2016) reports evidence of strong positive co-movements in the aftermath of the commodity boom. Rafiq and Bloch (2016) employ both linear and nonlinear Autoregressive Distributed Lag models and asymmetric Granger causality tests on annual data from 1900 to 2011 and find significant effects of oil price on several agricultural and non-agricultural commodity prices. Given the rising role of biofuel business in strengthening the linkage between energy and commodity cereals, several studies have emerged on the subject. Du et al. (2011) show that the boom in ethanol production in late 2006 intensified the market integration between crude oil, corn, and wheat prices. Fernandez-Perez et al. (2016) use a structural VAR model and show that crude oil price have a unidirectional effect on the prices of corn, soybean, and wheat. The authors also report bi-directional effects between corn and wheat, and indicate that the linkages across the examined variables is stronger during periods of high oil prices. An interesting empirical study by de Nicola et al. (2016) indicates strong co-movements between the prices of 11 major energy, agricultural, and commodities from 1970-2013 and points toward the expansion of the biofuel industry and its important role in intensifying those co-movements. Huchet and Fam (2016) highlight the effects of financialization and speculation on the energy and agricultural commodity markets. As shown above, several factors such as changes in the macroeconomic uncertainty, the expansion of biofuel production, and the financialization and speculation in the commodity markets have played a significant role in intensifying price fluctuations in the energy and agriculture commodity markets. Furthermore, most of the existing literature relies on historical volatility measures and overlooks the market expectations of near-term volatility taken from option prices as in the case of the CBOE implied volatility indices. The rare studies that used implied volatility have so far ignored the energy-agricultural nexus and focused only on the oil-stock nexus (Maghyereh et al., 2016), or the gold-oil nexus (Bouri et al., 2017). To address this void in the financial literature, we use implied volatility indices in assessing the causal relation across crude oil, wheat and corn markets. Further, the above review shows that most of prior studies have used different econometric methods such as cointegration, non-linear and linear Granger time-domain causality, and multivariate GARCH modelling. We instead use the frequency-domain causality approach of Breitung and Candelon (2006) which decomposes the causality across the implied volatility indices at different frequencies and thus uncovers the differences between short, medium, and long-run causalities, an unexplored research area.

3. Testing methodology and data

This section describes the empirical model and the data set.

3.1 Frequency domain causality

A variable X is said to "Granger causes" another variable Y if lagged values of X contain information that helps predict Y. In addition to such a unidirectional causality running from X to Y, a bi-directional causality exists between these two variables if also the lagged values of Y contain information that helps predict the other variable X. Usually conducted with a VAR framework, Granger-causality serves as a simple yet powerful tool to examine information flow across variables, in both time and frequency domains. Although the Granger causality test in the time domain has been extensively used in the empirical literature, one of its central weaknesses relies in its restricted assumption that only one single statistical measure can be used to explain the relation among the examined variables at all frequencies (at an infinite time horizon). In this sense, there is enough evidence that the causal influence may change along the time and frequency domain (i.e. causality differs in the short, medium, and long run). Interestingly, Breitung and Candelon (2006) argue that causality at low frequencies may differ from that at high frequencies and decompose the causality at different frequencies. Notably, Breitung and Candelon (2006) based their test on the framework of Geweke (1982) and Hosoya (1991).[1]

Let $Zt = [Xt, Yt]$ a two-dimensional vector of endogenous variables observed at time $t = 1, \ldots,$ T, the vector has a finite order VAR representation such as

$$\theta(L)Z_t=\varepsilon_t \qquad (1)$$

where, $\theta(L)=1-\theta_1 L- \ldots -\theta_p L^p$ is a 2×2 lag polynomial with $L^k Z_t=Z_{t-k}$. The error term ε_t is assumed to be a white noise with zero mean and covariance matrix $E(\varepsilon t\ \varepsilon' t) = \Sigma$ defined positive. The matrix Σ is decomposed as $G'G=\Sigma^{-1}$, where G is the inferior triangular matrix of the Cholesky decomposition, such that $E(\eta_t\ \eta'_t) = I$, and $\eta_t = G\varepsilon_t$.

If the system is stationary, then the VAR process will have a moving average with the following presentation:

$$z_t = \phi(L)\varepsilon_t = \begin{pmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{pmatrix} \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$
$$= \varphi(L)\eta_t = \begin{pmatrix} \varphi_{11}(L) & \varphi_{12}(L) \\ \varphi_{21}(L) & \varphi_{22}(L) \end{pmatrix} \begin{pmatrix} \eta_{1t} \\ \eta_{2t} \end{pmatrix} \qquad (2)$$

where $\phi(L)=\theta(L)^{-1}$ and $\varphi(L)=\phi(L)G^{-1}$

Accordingly, the spectral density of X_t is given by:

$$f_x(\omega) = \frac{1}{2\pi}\{|\varphi_{11}e^{-i\omega})|^2 + |\varphi_{12}e^{-i\omega})|^2\} \qquad (3)$$

As defined by Geweke (1982) and Hosaya (1991), the measure of causality is defined as:

$$M_{y\to x}(\omega) = \log\left[1 + \frac{2\pi f_x(\omega)}{|\varphi_{11}(e^{-i\omega})|^2}\right]$$
$$= \log\left[1 + \frac{|\varphi_{12}(e^{-i\omega})|^2}{|\varphi_{11}(e^{-i\omega})|^2}\right] \qquad (4)$$

The above measure of causality can be used to test the null hypothesis that Y_t does not Granger cause X_t at frequency ω [$H_0 : M_{y\to x}(\omega)=0$]. The measure is zero if $|\varphi_{12}(e^{-i\omega})|^2=0$, suggesting that Y_t does not Granger cause X_t at frequency ω.

The statistic $M_{y\to x}(\omega)$ is obtained by replacing $|\varphi_{11}(e^{-i\omega})|$ and $|\varphi_{12}(e^{-i\omega})|$ in equation (4) by the estimated values obtained from the fitted VAR representation.[2]

Although, there is a voluminous empirical literature on the application of Granger causality in the time domain, to the best of our knowledge, no prior studies have uncovered the difference between high and low frequencies in the dynamics of the implied volatility causalities across crude oil, corn, and wheat markets. This notable frequency domain approach of causality has been recently applied to model the linkages among stock markets (Grandojevic and Dobardzic, 2013), and sunspot numbers and global temperatures (Gupta et al. 2015).

3.2 Data

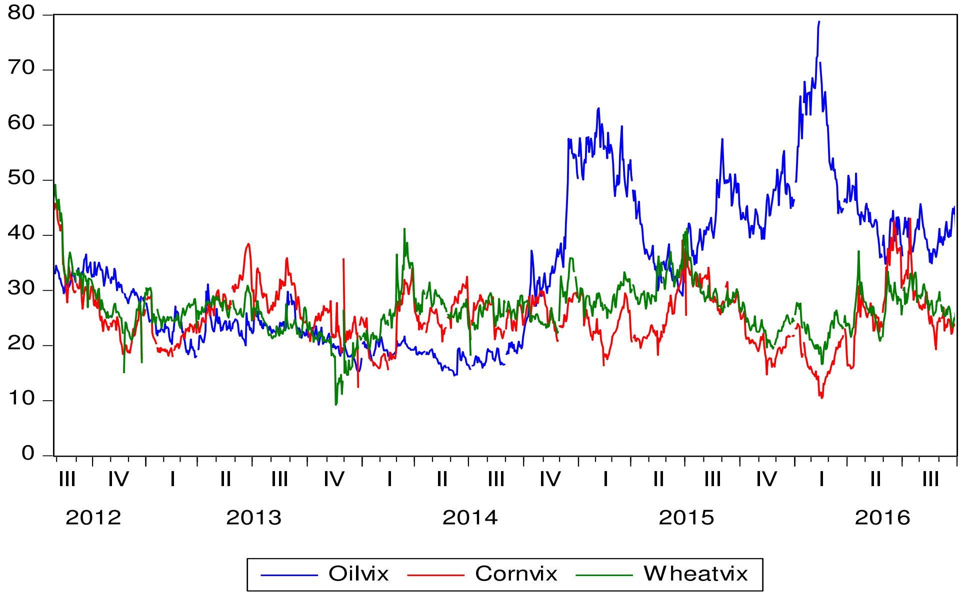
We use daily closing price for three implied volatility indices: the crude oil volatility index (*oilvix*), the corn volatility index (*cornvix*), and the wheat volatility index (*wheatvix*). Our study covers the period from July 27, 2012 to September 30, 2016, whose start is dictated by

[1] Lemmens et al. (2008) proposed an alternative Granger causality test over the spectrum based upon Pierce (1979). A simulation study suggests the test is less powerful than Breitung and Candeon (2006) test as long as the lag orders are appropriately chosen. Lemmens et al. (2008) recommends selecting orders based upon BIC.

[2] The reader can refer to Breitung and Candelon (2006) for a more detailed discussion about the frequency domain approach of causality.

the availability of data. The latter were compiled from DataStream. Interestingly, the sample period allows us to make causality inferences based on the recent volatility dynamics across crude oil, corn, and wheat markets beyond the usual focus on the global financial crisis of 2008 and food crisis of 2006-2008. However, Figure 1 shows that the three implied volatility indices exhibit large fluctuations over the entire period, especially for the case of crude oil.

Figure 1. Daily time evolution of implied volatility levels.



The summary statistics of the implied volatility of crude oil, wheat and corn series are provided in Table 1. The highest average mean and standard deviation of volatility are observed for crude oil. All series are found to be leptokurtic and skewed to the right. The results from two unit root tests, Augmented Dickey fuller (ADF) and Phillips Perron (PP), indicate that *cornvix* and *wheatvix* are stationary at the 1% significance level. As for *oilvix*, we use the first difference (*Δoilvix*) which is stationary. Given that the frequency domain causality approach requires stationary series, we therefore conduct the empirical analysis using the level series of *cornvix*, *wheatvix*, and the first difference (change) of *oilvix*.

Table 1: Summary statistics

	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	ADF	PP
Oilvix	33.324	78.970	14.500	13.327	0.626	2.598	1.948	1.769
ΔOilvix	0.000	0.278	-0.135	0.044	0.888	6.991	-31.661*	-31.883*
Cornvix	25.276	45.780	10.400	5.373	0.418	3.795	-5.254*	-5.598*
Wheatvix	26.676	49.220	9.190	4.617	0.525	5.688	-6.155*	-5.566*

Notes: This table provides the summary statistics and unit root tests for the implied volatility indices of crude oil (and its first difference), corn, and wheat. The sample period is from July 27, 2012 to September 30, 2016 and include 1052 daily observations. For Augmented Dickey fuller (ADF) and Phillips Perron (PP), the null hypothesis is that the series has a unit root; * denotes statistical significance at the 1% level.

However, it is well documented that the presence of structural breaks may affect the causality results. To illustrate, Henriques and Sadorsky (2008) failed to find a significant relationship between oil prices and stock prices of clean energy firms using January 3, 2001 – May 30, 2007 data. Kumar et al. (2012) extended the analysis with weekly data from April 22, 2005 to November 26, 2008 and found the stock prices are affected by oil prices. This result contrasts with Henriques and Sadorsky (2008) and suggests a possible structural break in the relationship between oil prices and stock prices of clean energy firms in the dataset. Mensi et al. (2014a) applied daily data from January 2, 1990 to September 18, 2012 to estimate a GARCH(1,1) model. Three structural breaks in the returns and three structural breaks in volatility were identified for both Brent index and WTI albeit the estimated break dates are slightly different across the four cases. Notably, July, September, October, and November in 2007 are all estimated as break dates. Using Bai and Perron's (2003) sequential and repartition tests on the crude oil equation, which includes one lag for *Δoilvix* and one lag for *cornvix*, we failed to detect a break. We also found no structural breaks for the case of *oilvix* and *wheatvix*. As for the *cornvix* equation, which comprises two lags for *wheatvix*, the structural breaks are found at May 1, 2013 and January 10, 2014; accordingly, for the causality analysis of the pair *cornvix–wheatvix*, we divide the entire period into three sub-periods.

4. Empirical results

4.1 Time domain causality results

Preceding the examination of the frequency domain causality, we conduct the conventional time domain Granger causality analysis calculated as a Wald test within the VAR framework. For the latter, we select the number of lagged variables based on SIC criterion. The results from Table 2 provide no evidence of a causal relation among the three variables under study for the entire period. As for the pair of *cornvix–wheatvix* in three sub-samples, we report evidence that *cornvix* Granger causes *wheatvix* at the 1% significance level in subsample 1. Furthermore, we show a bidirectional causality at the 10% level in sub-sample 2. As for the subsample 3, we find only a unidirectional causality running from *wheatvix* to *cornvix* at the10% level.

Table 2. VAR Granger causality test

	Sample	Null hypothesis	df	Chi-sq	*P* values
Oil-Corn	Full sample	*oildvix ≠› cornvix*	3	5.425	0.143
		cornvix ≠› oilvix	3	0.119	0.989
Oil-Wheat	Full sample	*oilvix ≠› wheatvix*	3	1.639	0.650
		wheatvix ≠› oilvix	3	2.413	0.491
Corn-Wheat	Full sample	*cornvix ≠› wheatvix*	5	8.865	0.114
		wheatvix ≠› cornvix	5	6.349	0.273
Corn-Wheat	Subsample 1	*cornvix ≠› wheatvix*	1	7.578	0.005
		wheatvix ≠› cornvix	1	0.057	0.810
Corn-Wheat	Subsample 2	*cornvix ≠› wheatvix*	3	6.638	0.084
		wheatvix ≠› cornvix	3	6.568	0.087
Corn-Wheat	Subsample 3	*cornvix ≠› wheatvix*	2	0.397	0.819
		wheatvix ≠› cornvix	2	5.755	0.056

Notes: This table tests the null hypothesis of no Granger causality. The degrees of freedom are determined by SIC. Subsample 1 spans from July 27, 2012 to May 1, 2013; subsample 2 spans from May 2, 2013 to 10 January, 2014; subsample 3 spans from January 11, 2014 to September 30, 2016.

4.2 Frequency domain causality results

Figures 2-7 depict the results from the frequency-domain test along the lines of Breitung and Candelon (2006), for the full sample and three sub-samples. The dashed line represents the 10% or 5% critical value, while the solid line characterizes the statistical test of all frequencies in the interval $(0,\pi)$. Further, the horizontal axis describes the frequency parameter omega (ω) which is used to calculate the length of the period T. The latter is measured in days and corresponds to a cycle where $T = 2\pi / \omega$. If the test statistic is below the 10% (5%) critical value, then the null hypothesis of no causality is rejected for the corresponding frequency, and vice versa.

Figure 2. Frequency domain causality between ΔOilvix and Cornvix

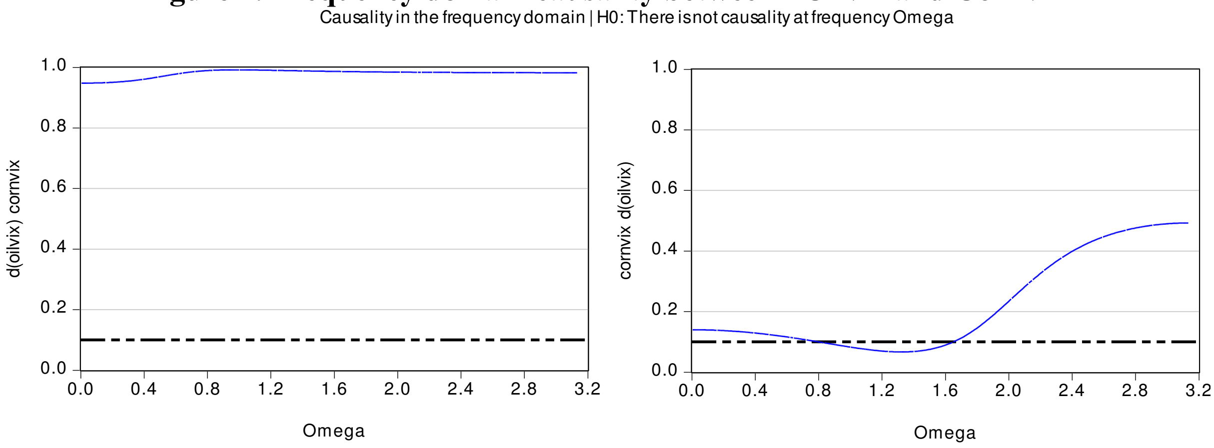


Figure 3. Frequency domain causality between ΔOilvix and Wheatvix

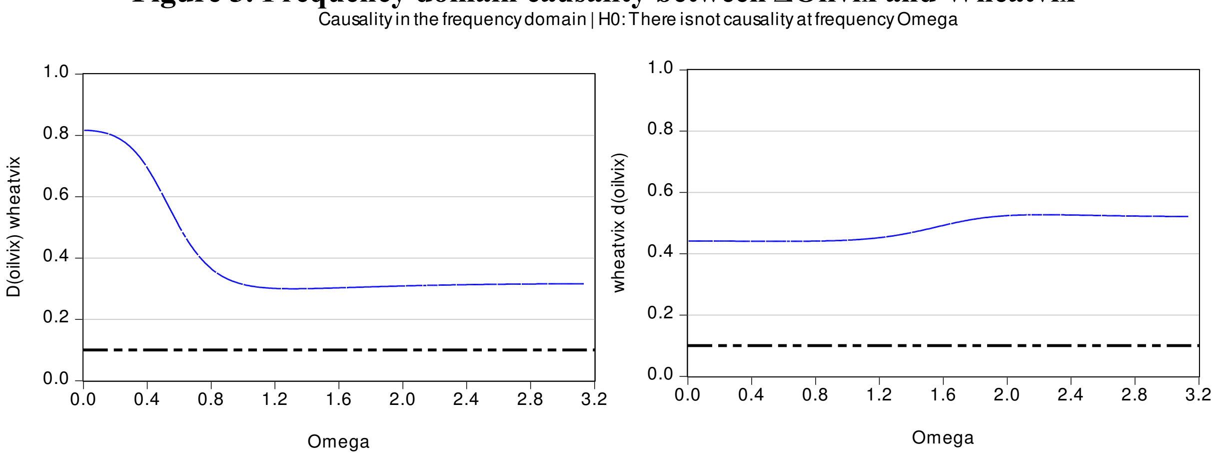
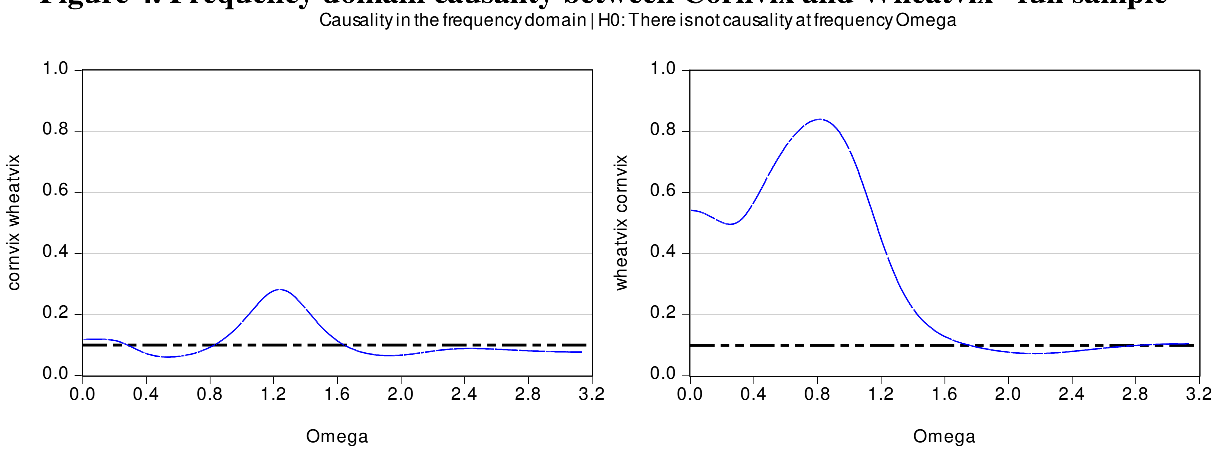


Figure 4. Frequency domain causality between Cornvix and Wheatvix –full sample



For the entire period Figures 2-4 present the estimation results from the frequency-domain causality, where the most suitable maximum number of lags was fixed at three. As shown in Figure 2, *oilvix* changes Granger cause *cornvix* at the 10% significance level in medium frequencies of 0.8 to 1.6, corresponding to a wave ranging from four to eight days; and there is no evidence of any feedback effects. Accordingly, the changes in implied volatility of the crude oil market can be used to predict the implied volatility of the corn market in medium frequencies. This result may be explained by the dominance effect of the crude oil market on the corn market, as reported in the existing literature (e.g. Mensi et al., 2014b). In Figure 3, there is no evidence of causality between *oilvix* changes and *wheatvix*. As for the pair of *cornvix-wheatvix*, Figure 4 clearly shows evidence at the 10% significance level of a bi-directional causal effect between *wheatvix* and *cornvix* that differs across frequencies. This latest finding adds to the bi-directional effects between corn and wheat markets reported by Fernandez-Perez et al. (2016).
Overall, the above results for the full period indicate that the causal relation between the implied volatility indices across crude oil, corn, and wheat markets vary across time and frequency, which is important in terms of hedging strategies and portfolio risk management.

Figure 5. Frequency domain causality between Cornvix and Wheatvix –subsample 1

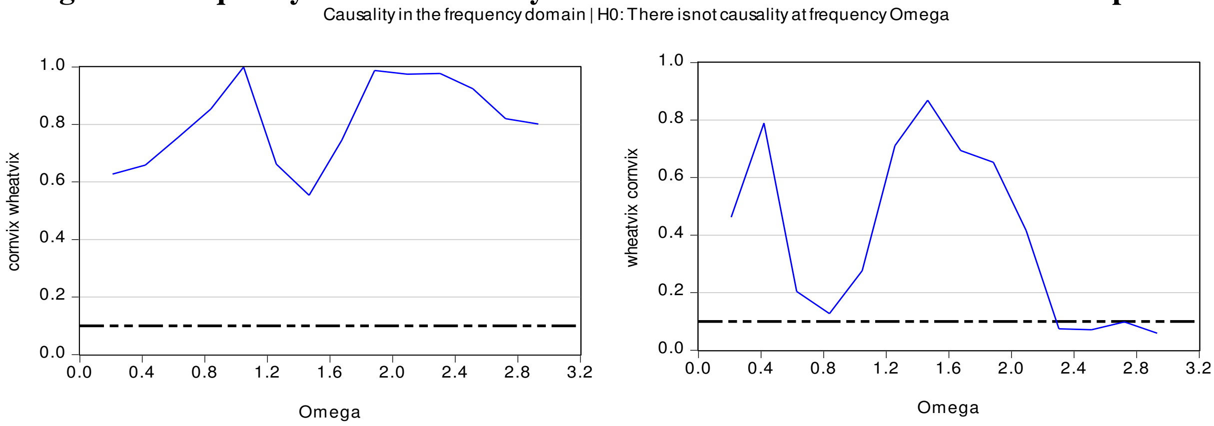


Figure 6. Frequency domain causality between Cornvix and Wheatvix –subsample 2

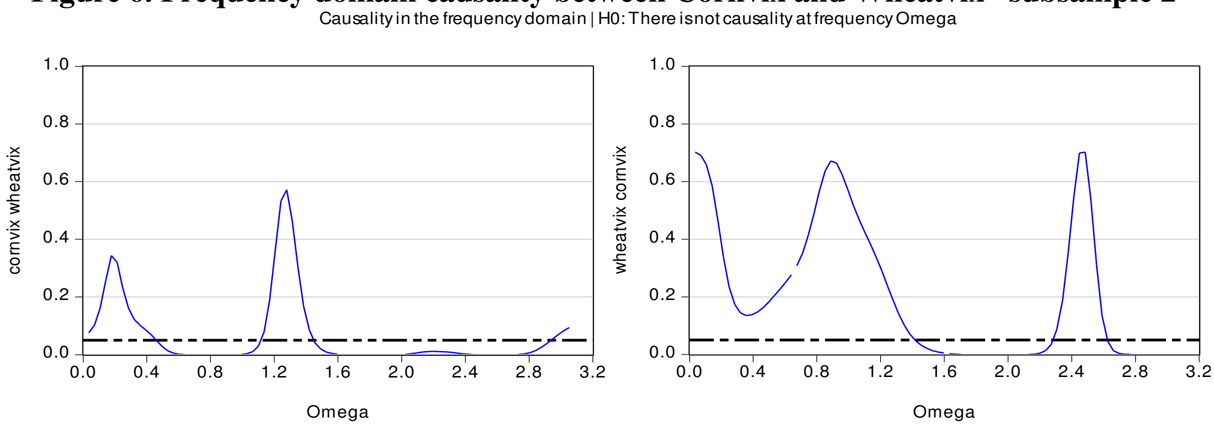
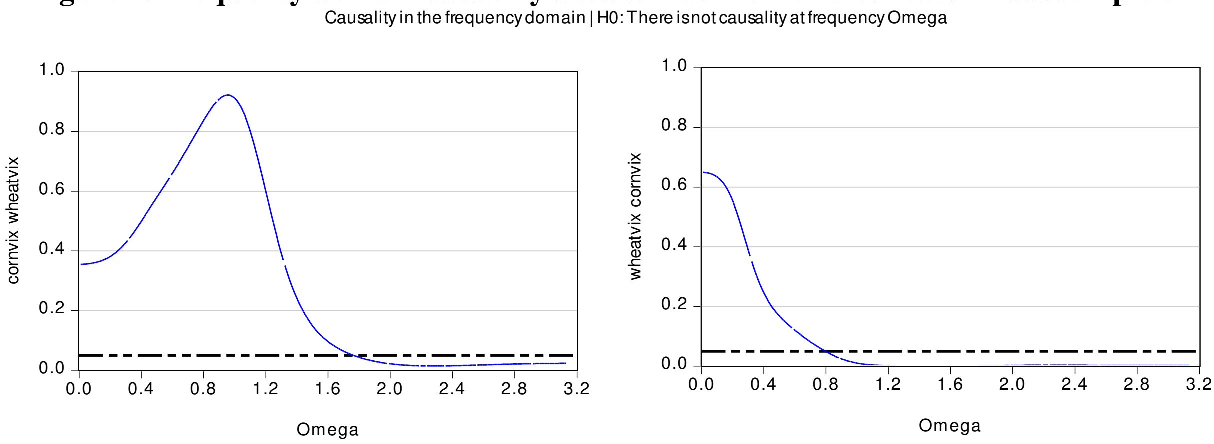


Figure 7. Frequency domain causality between Cornvix and Wheatvix –subsample 3



Given the presence of two structural break points in the relation between *cornvix* and *wheatvix*, we divide the full sample accordingly into three subsamples and re-examine the frequency domain causality (Figures 5-7). In subsample 1, Figure 5 shows that at the 5% level *cornvix* Granger causes *wheatvix* in long frequencies higher than 2.3, corresponding to a period of three days. In contrast, in subsample 2, Figure 6 shows evidence of a bi-directional causality between *cornvix* and *wheatvix* in different frequencies at the 5% significance level. Furthermore, in subsample 3, Figure 7 also reveals that, at the 5% level, *wheatvix* Granger causes *cornvix* in medium and high frequencies, corresponding to a period of two to five days; whereas the reverse causality is for low, medium, and high frequencies, corresponding to a period of two to eight days. These findings suggest that the inter-predictability between *cornvix* and *wheatvix* is affected by the presence of structural breaks and thus differs across the different subsamples. Furthermore, the findings highlight the role of the cycle-length in linking between the two cereal implied volatility indices for potential Vega hedging strategies.

5. Conclusion

Unlike most of prior studies, we use the newly introduced implied volatility indices–derived from option prices–to examine the linkages across crude oil, corn and wheat prices over the period July 27, 2012 to September 30, 2016. Implied volatility reflects information that a model–based historical volatility could not, and represents a forward-looking measure of market uncertainty. Econometrically, we employ the frequency domain causality (Breitung and Candelon, 2006) which decomposes the causality at different frequencies and thus allows the causality at low frequencies to differ from that at high frequencies.

The empirical analyses provide some interesting findings. First, we find that the results from the frequency–domain analysis are different and more nuanced than the time–domain causality technique. Second, medium-run causalities exist between *oilvix* changes and *cornvix*, while no causality is found between *oilvix* changes and *wheatvix*, suggesting that changes in the implied volatility of crude oil predict only the corn implied volatility in some frequencies. These findings, which show that the causal relation across the implied volatility indices of crude oil and corn differs between frequencies, complement prior studies (e.g. Du et al., 2011; Mensi et al., 2014b) and intuitively point toward the dominant effect played by the crude oil market on the corn market. Third, the findings emphasize the importance of accounting for detection structural breaks in the causality analysis between the implied volatility indices of corn and wheat commodities, and thus nicely complement Fernandez–

Perez et al. (2016). While overall results highlight the importance of using the frequency domain causality approach for uncovering short- and long-run linkages across the implied volatilities of oil and cereal commodities, we stress on the importance of detecting structural breaks in the spectral causality analysis between the implied volatilities of corn and wheat markets.

Traders, portfolio managers, and policy-makers can build on our abovementioned findings in managing the risk associated with energy and cereal commodities. This is particularly important given the emergence of implied volatility linked products as risk management tools to facilitate Vega hedging in the crude oil-cereal commodity markets and within cereal commodities. As such, traders and investors can also use our empirical findings to construct Vega neutral strategies to minimise the risk level of an option portfolio. Practically, the benefits of hedging strategies in the energy and cereal commodity markets can still be exploited as a consequence of the reported evidence of weak linkages in some high and low frequencies.

Finally, we offer some caveats regarding the methodology adopted in this paper. In general, the results from Granger causality test depend upon the choice of the lag orders. There exists a tradeoff such that a smaller lag produces smaller variance but confronts a risk of bias whereas a larger lag reduces the bias problem at the cost of efficiency. In the case of long memory time series, the lag order would be very large. A parsimonious model such as VARFIMA (vector autoregressive fractionally integrated moving average) is preferred. The fractional integration order is determined by the Hurst exponent. In other words, Hurst exponent dictates the model specification for the Granger causality test. Test methods are provided in Chen (2006, 2015). In our paper, we restrict ourselves to integration order, i.e., I(0) and I(1), and fix the lag order at the maximum of three. A more reliable analysis can be undertaken allowing for fractional integration. In addition, the Breitung and Candelon test can detect only linear Granger causality. Hlavá˘cková-Schindler et al. (2007) construct a nonparametric test with Shannon entropy to detect nonlinear Granger causality[3]. Both Hurst exponent and Shannon entropy can be applied to evaluate market efficiency. Indeed, Mensi et al. (2014a) calculate the two measures for two crude oil price indices, European Brent index and WTI, and find the former is less inefficient than the latter.

A structural break identified with Bai and Perron (2003) accommodates the difference before and after the break date. Time is the only determining factor for the dynamic process. An endogenous structural change can be described by a Markovian switching (MS) VAR model. Under this specification, there are two states and different price processes prevail across the two states. The state transition probability is described by a constant matrix. Managi and Okimoto (2013) adopt a two-state MSVAR model and find a structural change during November and December of 2007. While MSVAR model is preferred to the Bai-Perron approach to capture structural change, it is cumbersome to extend the Breitung and Candelon test form the VAR to MSVAR framework. Pataracchia (2011) and Cavicchioli (2013) provide spectral representation for MSVARMA models. The final expressions for the Breitung-Candelon non-causality restrictions are too complicated to be useful for direct implementation. This topic will be left for future research.

[3] Testing for nonlinear Granger causality was first proposed in Hiemstra and Jones (1994) and then modified by Diks and Panchenko (2006). The test statistics are based upon correlation integral.

References

Baffes, J. (2007). Oil spills on other commodities. Resources Policy, 32(3), 126-134.

Bai, J. and Perron, P. (2003). Computation and analysis of multiple structure models. Journal of Applied Econometrics, 18, 1-22.

Breitung, J. and Candelon, B. (2006). Testing for short-and long-run causality: A frequency-domain approach. Journal of Econometrics, 132(2), 363-378.

Bouri, E., Jain, A., Biswal, P.C. and Roubaud, D. (2017). Cointegration and nonlinear causality amongst gold, oil, and the Indian stock market: Evidence from implied volatility indices. Resources Policy, 52, 201-206.

Cavicchioli, M. (2013). Spectral density of Markov switching VARMA. Economics Letters, 121, 218-220.

Chen, W. (2006). Estimating the long memory Granger causality effect with a spectrum estimator. Journal of Forecasting, 25, 193–200.

Chen, W. (2015). Estimate long memory causality relationship by wavelet method. Computational Economics, 45, 531–544

de Nicola, F., De Pace, P. and Hernandez, M.A. (2016). Co-movement of major energy, agricultural, and food commodity price returns: A time-series assessment. Energy Economics, 57, 28–41.

Diks, C. and Panchenko, V. (2006). A new statistical and practical guidelines for nonparametric Granger causality testing. Journal of Economic Dynamics & Control, 30, 1647-1669.

Du, X., Yu, C. and Hayes, D. (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: a Bayesian analysis. Energy Economics, 33(3), 497–503.

Fernandez-Perez, A., Frijns B. and Tourani-Rad, A. (2016). Contemporaneous interactions among fuel, biofuel and agricultural commodities. Energy Economics, 58, 1–10.

Geweke, J. (1982). Measurement of linear dependence and feedback between multiple time series. Journal of the American statistical association, 77(378), 304-313.

Grandojevic, N. and Dobardzic, E. (2013). Causality between regional stock markets: A frequency domain approach. Panoeconomicus, 5, 633-647.

Gupta, R., Gil-Alana, L. A. and Yaya, O. S. (2015). Do sunspot numbers cause global temperatures? Evidence from a frequency domain causality test. Applied Economics, 47(8), 798-808.

Henriques, I. and Sadorsky, P. (2008). Oil price and the stock prices of alternative energy companies. Energy Economics, 30, 998-1010.

Hiemstra, C. and Jones, J. D. (1994). Testing for linear and nonlinear Granger causality in price-volume relation. Journal of Finance, 49, 1639-1664.

Hlaváˇcková-Schindlera, K., Palušb, M., Vejmelkab, M. and Bhattacharyaa, J. (2007). Causality detection based on information-theoretic approaches in time series analysis. Physics Reports, 441, 1-46.

Hosoya, Y. (1991). The decomposition and measurement of the interdependency between second-order stationary processes. Probability theory and related fields, 88(4), 429-444.

Huchet, N. and Fam, P.G. (2016). The role of speculation in international futures markets on commodity prices. Research in International Business and Finance, 37, 49-65.

Jiang, G. J. and Tian, Y. S. (2005). The model-free implied volatility and its information content. Review of Financial Studies, 18(4), 1305-1342.

Kumar, S., Managi, S. and Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: a vector autoregression analysis. Energy Economics, 34, 215-226.

Lemmens, A., Croux, C. and Dekimpe (2008). Measuring and testing Granger causality over the spectrum: an application to European production expectation surveys. International Journal of Forecasting, 24, 414-431.
Lucotte, Y. (2016). Co-movements between crude oil and food prices: A post-commodity boom perspective. Economics Letters, 147, 142-147.
Maghyereh, A.I., Awartani, B. and Bouri E. (2016). The directional volatility connectedness between crude oil and equity markets: new evidence from implied volatility indexes. Energy Economics, 57, 78–93.
Managi, S. and Okimoto, T. (2013). Does the price of oil interact with clean energy prices in the stock market? Japan and the World Economy, 27, 1-9.
Mensi, W., Beljid, M. and Managi, S. (2014a). Structural breaks and time-varying levels of weak-form efficiency in crude oil markets: evidence from the Hurst exponent and Shannon entropy methods. International Economics, 140, 89-106.
Mensi, W., Hammoudeh, S., Nguyen, D.K. and Yoon, S.-M. (2014b). Dynamic spillovers among major energy and cereal commodity prices. Energy Economics, 43, 225–243.
Pataracchia, B. (2011). The spectral representation of Markovian switching ARMA models. Economics Letters, 112, 11-15.
Pierce, D. (1979). R-squared measures for time series. Journal of the American Statistical Association, 74, 901-910.
Rafiq, S. and Bloch, H. (2016). Explaining commodity prices through asymmetric oil shocks: Evidence from nonlinear models. Resources Policy, 50, 34-48.