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Price volatility spillovers among agricultural commodity and crude oil markets: Evidence from the range-based estimator

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Abstract: The paper examines the price volatility spillovers among the crude oil, soybeans, corn, wheat, and sugar futures markets over the period 1/1/2006–11/29/2013. We separately investigate the periods of the pre-crisis, the crisis, and the post-crisis in financial markets. We use the Yang-Zhang estimators for the historical volatility and find that there is a volatility sprawl from the crude oil to corn markets. There is also bi-directional causality between the corn and soybeans markets. In addition, we observe significant volatility spillovers from both the soybeans and the corn markets to the wheat markets. The results are also valid in a different sub-period analysis.

Key words: agricultural commodity market, financial crisis of 2008–2009, futures markets, historical price volatility, intra-day data

Do the fluctuations in one commodity price carry over to another commodity price? Answering this question has been a growing issue in the recent literature, and indeed, there is an abundant evidence elucidating the transmission mechanism among the prices of energy and the agricultural commodity markets (Pokrivcak and Rajcaniova, 2011; Gozgor and Kablamaci 2014).[1] For instance, Gozgor and Kablamaci (2014) recently investigated the relationship between crude oil and 29 agricultural commodity prices. Taking role of the US Dollar and the perceived global market risks into consideration, they find that the oil price has unidirectional and positive impacts on almost all agricultural commodity prices.

The objective of this paper is to examine the price volatility spillovers among the energy and agricultural commodity markets. For this purpose, we focus on the volatility spillovers among the futures markets of the crude oil, soybeans, corn, wheat, and sugar for the period from January 1, 2006 to November 29, 2013 in the global commodity crisis era. We focus on the price volatility transmission between crude oil and soybeans, corn, wheat, and sugar. These are the "main crops" used in the biofuel production, and are the key food products worldwide[2] (Nazlioglu et al. 2013). Furthermore, according to Du et al. (2011), Hertel and Beckman (2012) and Trujillo-Barrera et al. (2012), agricultural commodities and crude oil prices show a low (or negative) correlation before 2006. Therefore, the analysis in this paper starts on January 1, 2006.[3] This study investigates the price volatility spillover dynamics in the crude oil and agricultural commodity markets. Indeed, the price fluctuations in the energy and commodity markets have importance in all open-economies, and a country can be affected with regard to its economic conditions. For example, the oil and agricultural commodity price volatility would affect the welfare earnings, i.e.,

[1]See Janda et al. (2012), Serra and Zilberman (2013) and Kristoufek et al. (2014) for the recent review on the biofuel-related price transmission literature of the energy and agricultural commodity markets.

[2]For the choice of the covered commodities, the previous paper on the literature review (see Serra and Zilberman 2013) and the formal preliminary statistical investigation can also be considered. For a suitable statistical approach to choosing the relevant commodities, see Kristoufek et al. (2012, 2013).

[3]The Renewable Fuel Standard of the Energy Policy Act in 2005 has a crucial role in the soaring ethanol production in the U.S. that leads to a higher production and demand for biofuels and this can be the main explanation of a stronger relationship between the oil and agricultural commodity prices after 2006.

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the consumption from imports and production from exports; because most of the tradable goods are still commodities. The price volatility of the agricultural commodity and energy markets can also be directly related to the real income, especially in developing economies and the least developed countries (LDCs).[4] On the other hand, not only the rising food prices, but also the food price volatility has a negative effect on poor people. Therefore, the energy and agricultural commodity prices and their volatility are crucial for the policy-makers, producers, and either empirical or theoretical studies.

In this paper, we construct our key hypothesis to test that the volatility in the crude oil markets significantly affects the volatility in one agricultural commodity market at least. To test the hypothesis, we use the Yang-Zhang range-based volatility estimators. In addition, we separately investigate the periods of the pre-crisis, the crisis, and the post-crisis in global financial markets and run the Granger causality test procedures for the price volatility values. This paper focuses on the relatively higher frequency intraday data, for the reason stated by Andersen et al. (2003) that an examination of price volatility should be based on the high-frequency data. This idea comes from their findings that the high-frequency price volatility is easier to predict and the examination of the price volatility should rely on the available data that has the highest frequency Andersen et al. (2003) and Serra (2013). In addition, in turbulent days with respect to the big losses and recoveries in the commodity markets, the classical close-to-close volatility models, such as the stochastic volatility or the Generalized Autoregressive Conditional Heteroskedasticity (GARCH), would introduce low price fluctuations, while the daily price range estimators can successfully indicate that there is a high-level price volatility (Chou et al. 2010). Furthermore, from the theoretical point of view, the range-based estimators introduce a more efficient estimator of the historical price volatility than the price return (Chou et al. 2010). Therefore, we focus on the historical range-based volatility estimator of the Yang-Zhang and neglect the GARCH-type models in the empirical analysis. We suggest that our empirical results those are based on that the price volatility spillover mechanisms would be important not only for the policy makers and producers but also for the investors, traders, speculators, risk management issues, portfolio diversifications, and hedging strategies. This issue comes from the fact that volatility is a decisive and fundamental factor in the futures and options markets as well as other complex derivative products[5] (Chkili et al. 2014).

The contributions of this paper to the existing literature are as follows. First, to the best of our knowledge, this paper represents the first study that considers the high-frequency intraday data and the range-based volatility estimator of the historical volatility in the literature.[6] To this end, we use the Yang-Zhang range-based volatility estimator. Second, we separate our whole sample into three sub-periods to examine the interrelationship among the crude oil, soybeans, corn, wheat, and sugar futures markets. We run the whole sample with the Yang-Zhang range-based volatility estimator first and then split the sample and use the Yang-Zhang range-based volatility estimator on each part. Thus, in a way, we check whether our empirical results are period-specific or not.

DATA AND METHODOLOGY

Data

This paper focuses on the period from 1/1/2006 to 11/29/2013 (1990 observations) in a high-frequency (open-high-low-close prices) data set. According to Du et al. (2011), Hertel and Beckman (2012), Trujillo-Barrera et al. (2012) and Nazlioglu et al. (2013), the period after 2006 is the only era that introduces a significant interaction among the crude oil and agricultural commodity markets mainly due to the biofuels production and the role of speculation. Therefore, this paper covers and underlines this period not only following these evidences, but also we have limited the high-frequency data for the period before 2006. Furthermore, to investigate the different possible dynamics between the crude oil and each agricultural commodity market for the pre-crisis, the post-crisis

[4] It is important to note that the price volatility of the agricultural commodity and energy markets affecting the real income mainly depends on a specific country context.

[5] Kristoufek (2014) recently states that the long-memory effect is important for the crude oil price volatility. His paper also documents the important leverage effect that is highly relevant for the high-frequency data in this paper.

[6] See recent literature reviews in Serra (2013) and Serra and Zilberman (2013).

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Table 1. Descriptive Summary Statistics for the Close Price Log Returns (1/1/2006–11/29/2013)

Commodity	Mean	Std. Dev.	Minimum	Maximum
Crude Oil (WTI)	0.0002	0.0241	–0.1307	0.1641
CBOT Soybeans	0.0003	0.0189	–0.2341	0.2032
CBOT Corn	0.0003	0.0228	–0.2686	0.2028
CBOT Wheat	0.0002	0.0233	–0.0997	0.1017
ICE Sugar#11	0.00001	0.0192	–0.1411	0.0795

Data source: Bloomberg. WTI = West Texas Intermediate (New York, units: USD/bbl.), CBOT = Chicago Board of Trade (Chicago, units: USD/bu.), and ICE = Intercontinental Exchange (NASDAQ, units: U.S. cents per pound), referring to futures prices. We report the average returns and their standard deviation as well as the maximum and minimum returns at the daily-close prices.

and the period of global financial crisis in 2008, we cut our sample data into three sub-periods. Accounting for the boom-and-bust cycle in the commodity markets and also following Jin and Fan (2012), we consider July 31, 2008 and June 1, 2010 as the dates to be used to divide our sample. Thus, we define the pre-crisis period as from January 1, 2006 to July 31, 2008 (653 observations) and the financial crisis period from August 1, 2008 to May 31, 2010 (457 observations), and the post-crisis sample covers the period from June 1, 2010 to November 29, 2013 (888 observations)[7]. In short, we analyse the price volatility transmission separately for the whole period of January 1, 2006–November 29, 2013 as well as for three sub-periods. We focus on the futures market data and obtain them from the data source of Bloomberg. We report the descriptive summary statistics and brief details on the data in Table 1.

Historical range-based volatility estimators

As noted by Andersen (2000) and Andersen et al. (2003), the volatility estimators that are based on price intervals in a trading day can be an advantage to capturing the price fluctuations compared to other types of the volatility models. The intra-day data are now easier to obtain for both the energy and agricultural commodity markets; and therefore, we attempt to use the Yang-Zhang historical range-based volatility estimators in this class. Basically, these estimators use information on the daily trading ranges – the intraday open, close, high, and low prices–for a specific commodity. Their notations for the related parameters in the range-based volatility estimators are stated as follows: O_t is the open price on day t, C_t is the close price on day t, H_t in C_t is the high price within t days, and L_t is the low price within t days. In addition, the logarithmic returns (r_t) are calculated as (r_i = (ln C_{t+1}/C_t), where the average returns ($\bar{r}$) are calculated as $\bar{r} = (r_1 + r_2 + \ldots r_{n-1})/n-1$. Furthermore, the classical historical volatility is defined as $\sigma = \sqrt{\frac{Z}{n-2}\sum_{t=1}^{n-1}(r_t - \bar{r})^2}$.

In these equations, n indicates the number of historical days to calculate the price volatility, and Z is the number of days that have close prices in the historical annual data. Z is 252 days in the paper.

Following these definitions, the range volatility is defined as the difference between the high and the low price within t days, which can be written as $R_t = \ln(H_t) - \ln(L_t)$. While using this fundamental idea in the last equation, several range-based estimators of the historical volatility have been proposed to define the intraday (open-high-low-close) data (Chou et al. 2010).

At this stage, we briefly explain the historical range-based volatility estimators. For example, Parkinson (1980) defines an estimator that is based on the evidence that the intraday price intervals give much more information on the future volatility rather than two random points in a series. The estimator can be written as follows:

$$\sigma_p = \sqrt{\frac{Z}{n4\ln 2}\sum_{t=1}^{n-1}(\ln\frac{H_i}{L_i})^2} \tag{1}$$

Similarly, Garman and Klass (1980) offer a volatility estimator that is based on the information of the

[7]Different approach of dividing the data sample into subsamples can also be considered. For instance, Pomenkova and Marsalek (2012) and Kapounek and Pomenkova (2013) recently introduce the time-frequency approaches on the financial data. Following them, Vacha et al. (2013) consider the time-frequency approach of the wavelet analysis on the biofuels related agricultural commodity and oil prices. The wavelet analysis in such a way allows both for the local analysis of correlation among the related commodity prices and for the investigation of the direction of the co-movement through the phase difference.

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open, high, low, and close prices in a trading day. This estimator generates estimations that are assumed not to be included in the price jumps at the market opening, and this approach is based on a historical Brownian motion process without drift. The estimator can be shown as follows:

$$\sigma_{GK} = \frac{Z}{n}\sum\sqrt{\frac{1}{2}(\ln\frac{H_i}{L_i})^2 - (2\ln 2 - 1)(\ln\frac{C_i}{O_i})^2} \qquad (2)$$

Rogers and Satchell (1991) also add a drift term to their stochastic volatility estimator, and they assume that there is no jump or leap in the market opening. Using the high-low-open-close prices, they propose a new estimator that can be simply written as follows:

$$\sigma_{RS}^2 = \sigma\sqrt{\frac{Z}{n}\sum\left[\ln\frac{H_i}{C_i}\ln\frac{H_i}{O_i} + \ln\frac{L_i}{C_i}\ln\frac{L_i}{O_i}\right]} \qquad (3)$$

In addition, Yang and Zhang (2000) develop a continuous-time volatility estimator in the case of the presence of a jump in or a leap in the market opening and the Yang-Zhang estimator is independent from the drift parameter and is neutral to it. The Yang-Zhang estimator can be considered to be a weighted average of the Rogers-Satchell estimator, with regard to the open and close prices. The Yang-Zhang estimator can be explained as follows:

$$\sigma^2 = \sigma_o^2 + k\sigma_c^2 + (1-k)\sigma_{rs}^2 \qquad (4)$$

In this equation, $k = 0.34/[1 + (n + 1)/(n - 1)]$,

$\sigma_o^2 = \frac{Z}{n-1}\sum\left(\ln\frac{O_i}{C_{i-1}} - \mu_o\right)$, $\mu_o = \frac{1}{n}\sum\ln\frac{O_i}{C_{i-1}}$,

$\sigma_c^2 = \frac{Z}{n-1}\sum\left(\ln\frac{C_i}{O_i} - \mu_c\right)$, $\mu_c = \frac{1}{n}\sum\ln\frac{C_i}{O_i}$,

and the estimator can be written in detail, as follows:[8]

$$\sigma_{ZY}^2 = \frac{Z}{n}\sum\left(\ln\frac{H_i}{C_i}\ln\frac{H_i}{O_i} + \ln\frac{L_i}{C_i}\ln\frac{L_i}{O_i}\right) \qquad (5)$$

Empirical model and the Granger causality test procedure

Using the low-frequency data, this paper performs the Granger-Wald causality tests to measure the price volatility spillovers among the crude oil and agricultural commodity markets based on the multivariate system that includes all of the commodity prices. When we consider the stationary and uncorrelated series, the co-integration methodology would not be applicable. Our Granger-Wald causality test implementations are based on the Yang-Zhang estimators of the historical volatility. We implement the Granger causality analysis on the original volatility series. However, the trade volumes in crude oil markets are higher than in the agricultural commodity markets; therefore, the way of causality would run from the oil markets to soybeans, corn, wheat, and sugar markets (Trujillo-Barrera et al. 2012). Therefore, in our model, price shocks in the soybeans, corn, wheat, and sugar markets would be affected by shocks in all of the agricultural commodity markets, including crude oil, but they will have no effect on the crude oil market. Following Harri and Hudson (2009) and Natalenov et al. (2013), we identify the model to examine the price volatility spillover relationships in the residuals of the range-based volatility estimators among the crude oil and agricultural commodity markets using the Granger-Wald causality tests. To measure the price volatility spillovers among the crude oil (cr), soybeans (sb), corn (co), wheat (wh), and sugar (sg) markets, following Trujillo-Barrera et al. (2012) and Wu et al. (2011), we define our model as follows:

$$\Delta cr_t = E[\Delta cr_t | I_{t-1}] + e_{cr,t} \qquad (6)$$

$$\begin{bmatrix} sb_t \\ co_t \\ wh_t \\ sg_t \end{bmatrix} = \begin{bmatrix} E[\Delta sb_t | I_{t-1}] \\ E[\Delta co_t | I_{t-1}] \\ E[\Delta wh_t | I_{t-1}] \\ E[\Delta sg_t | I_{t-1}] \end{bmatrix} + \begin{bmatrix} \varepsilon_{sb,t} \\ \varepsilon_{co,t} \\ \varepsilon_{wh,t} \\ \varepsilon_{sg,t} \end{bmatrix} \qquad (7)$$

$$\begin{bmatrix} \varepsilon_{sb,t} \\ \varepsilon_{co,t} \\ \varepsilon_{wh,t} \\ \varepsilon_{sg,t} \end{bmatrix} = \begin{bmatrix} \phi_t \\ \omega_t \\ \theta_t \\ \vartheta_t \end{bmatrix} + \begin{bmatrix} e_{sb,t} \\ e_{co,t} \\ e_{wh,t} \\ e_{sg,t} \end{bmatrix} \qquad (8)$$

In Equation (6), the crude oil price volatility shocks are external, and these shocks would start the volatility transmission mechanism; then, other markets would react and interact. Here, Δ is the first difference operator, and the change in the crude oil prices at t (cr_t) is somewhat equal to a conditional expected change in the crude oil price when considering the affected information at $t - 1$ (I_{t-1}) plus the random shock

[8]See Shu and Zhang (2006) for details on the implementation of the range-based estimators of the historical volatility. In addition, Shu and Zhang (2006) show robustness of the Yang-Zhang estimator for the actual futures market data. Following their evidence, we use the Yang-Zhang estimator of the historical volatility.

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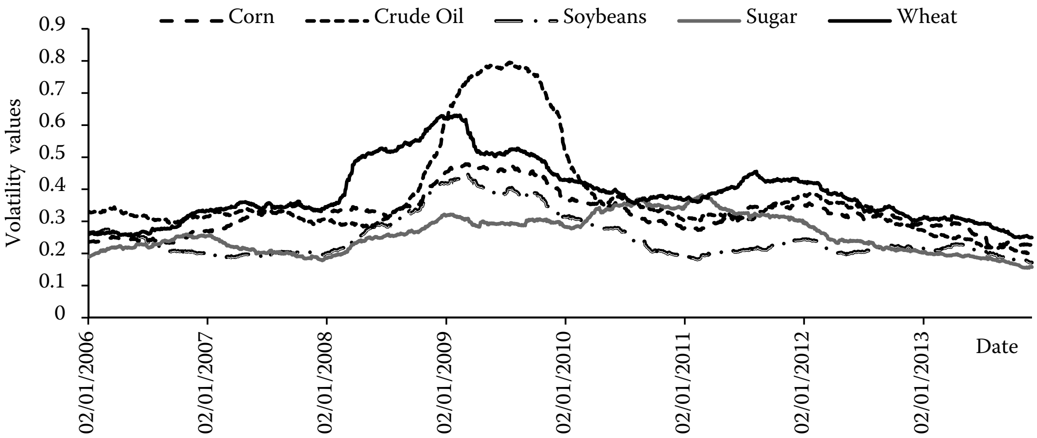

Figure 1. Graphs of the volatility values of the Yang-Zhang estimator (1/1/2006–11/29/2013)

($e_{cr,t}$). In Equation (7), the soybeans, corn, wheat, and sugar prices at t are equal to a sum of the conditional expected prices in the crude oil price with the affecting information at $t - 1$ (I_{t-1}), including the random shocks ($\varepsilon_{sb,t}$, $\varepsilon_{co,t}$, $\varepsilon_{wh,t}$, $\varepsilon_{sg,t}$). Equation (8) explains the details of the random shocks of the soybeans, corn, wheat, and sugar markets. There are two terms; the first term is the exogenous random shock of the crude oil ($\varepsilon_{cr,t}$), and the spillover coefficient for each market is ϕ_t, ω_t, Θ_t, and ϑ_t, respectively. The second term is the idiosyncratic errors of the soybeans, corn, wheat, and sugar markets $e_t = [e_{sb,t}, e_{co,t}, e_{wh,t}, e_{sg,t}]$; those can be mutually correlated, but they are uncorrelated to the crude oil innovation (Trujillo-Barrera et al. 2012).

EMPIRICAL RESULTS

We first report the results of the Granger causality test for the Yang-Zhang estimators for the whole sample in Table 2.[9] In addition, we show the volatility values of the range-based estimator of the Yang-Zhang for the whole period (1/1/2006-11/29/2013) in Figure 1.

The results for the Yang-Zhang estimators of the historical volatility indicate a unidirectional Granger causality from the crude oil to corn markets under the 5% significance level. In addition, there is a bidirectional spillover between the soybeans and corn markets. Furthermore, the price volatility in both the soybeans and corn markets significantly causes the volatility in the wheat market at the 5% significance level. We then report the results of the Granger causality test for the Yang-Zhang estimators for the pre-crisis sample in Table 3. We also report the results of the Granger causality test for the Yang-Zhang estimators of the historical volatility for the crisis sample. In addition, we show the results of the Granger causality test for the Yang-Zhang estimators for the post-crisis sample.

All of the results in Table 3, show that the price volatility transmission mechanisms are robust to different sub-periods. In addition, the results from Table 3 for the Yang-Zhang volatility estimators in-

Table 2. Results of the Granger Causality Tests for the Yang-Zhang estimator (1/1/2006–11/29/2013)

Granger Causality	(to) Soybeans	Corn	Wheat	Sugar
(from) Crude Oil	0.89 [0.3445]	4.23** [0.0417]	1.29 [0.2546]	0.04 [0.8349]
Soybeans	–	7.43*** [0.0064]	9.13*** [0.0025]	1.89 [0.1671]
Corn	21.6*** [0.0000]	–	8.50*** [0.0035]	0.99 [0.3177]
Wheat	0.17 [0.6787]	0.32 [0.5715]	–	2.39 [0.1218]
Sugar	0.01 [0.9593]	0.20 [0.6508]	0.74 [0.3866]	–

Test statistics and p-values are in brackets; ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively.

[9]We check the stationarity of the series in the empirical framework and all volatility series are stationary.

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Table 3. Results of the Granger causality tests for the Yang-Zhang estimator

Granger Causality	(to) Soybeans	Corn	Wheat	Sugar
(1/1/2006–7/31/2008)				
(from) Crude Oil	0.63 [0.4266]	9.47*** [0.0021]	0.20 [0.6526]	2.13 [0.1441]
Soybeans	–	9.35*** [0.0022]	8.60*** [0.0034]	0.20 [0.6541]
Corn	11.1*** [0.0000]	–	9.30*** [0.0023]	0.34 [0.5579]
Wheat	0.87 [0.3496]	0.17 [0.6748]	–	1.39 [0.2217]
Sugar	1.09 [0.2961]	1.29 [0.2548]	0.85 [0.3546]	–
8/1/2008–5/31/2010				
(from) Crude Oil	0.93 [0.3332]	5.27** [0.0209]	0.22 [0.6368]	0.08 [0.7745]
Soybeans	–	4.35** [0.0362]	4.20** [0.0391]	1.42 [0.2339]
Corn	9.21*** [0.0024]	–	3.77* [0.0523]	0.14 [0.7045]
Wheat	1.25 [0.2635]	0.03 [0.8487]	–	0.28 [0.5916]
Sugar	0.01 [0.9302]	0.01 [0.9681]	0.08 [0.7740]	–
6/1/2010–11/29/2013				
(from) Crude Oil	0.62 [0.4316]	9.56*** [0.0020]	1.23 [0.2668]	1.82 [0.1701]
Soybeans	–	8.50*** [0.0035]	19.2*** [0.0000]	1.22 [0.2682]
Corn	7.18*** [0.0073]	–	3.94** [0.0448]	0.07 [0.7890]
Wheat	1.52 [0.2170]	2.13 [0.1441]	–	0.54 [0.4622]
Sugar	0.05 [0.8271]	0.22 [0.6375]	0.43 [0.5085]	–

Test statistics and p-values are in brackets; ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively.

dicate that there is a unidirectional Granger causality from the crude oil to corn markets. Finally, we report a summary figure of the Granger causality results for the Yang-Zhang estimators in Figure 2.

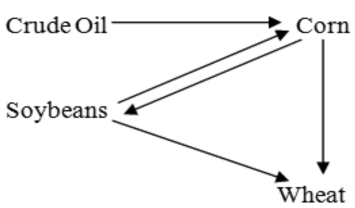

Figure 2. Summary of the results of the Granger causality tests for the Yang-Zhang estimator

CONCLUSION

This study examines the price volatility spillovers among the crude oil, soybeans, corn, wheat, and sugar futures markets. We also separately investigate the periods of the pre-crisis, the crisis, and the post-crisis in the global financial markets, and use the Yang-Zhang volatility estimators. The empirical results from the Granger causality test procedures indicate that there is a price volatility spillover from the crude oil to corn markets. There is also a bidirectional causality relationship between the corn and soybeans markets. In addition, we find significant price volatility spillovers from both the soybeans and corn markets to the wheat markets. These results are robust to the sub-periods analysis of the whole sample.

The results in this paper are in line with the previous studies of Harri and Hudson (2009), Trujillo-Barrera et al. (2012), and Wu et al. (2011), which have previously shown that there is a significant price volatility spillover from the crude oil to corn markets after 2006. It is noticeable that there is no price volatility spillover from the crude oil to the other commodity prices. This paper connects two global problems: hunger and poverty on the one hand and energy and climate change on the other and the results highlight the role of the biofuel production in the relationship between the crude oil and corn markets. Indeed, the actual volumes of crops being used for the energy production are related to the particular income groups that may be hurt and this will depend upon the availability of technologies and switching opportunities

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of these methodologies between the alternative fuels. In the recent study, Natalenov et al. (2013) indicate that two of three of the total production in corn has been used in the biofuel production after 2006, and this amount creates an additional volatility in the corn markets. In addition, crude oil can affect the corn markets via the costs of production and via the price speculation (Du et al. 2011).

Furthermore, there is a bidirectional price volatility spillover between the soybeans and corn markets. The interrelationship between the soybeans and corn markets can also be explained by the biofuel production (from corn as bioethanol and from soybeans as biodiesel). However, the crude oil markets do not directly affect the soybeans market, and these results are in line with the findings of Harri and Hudson (2009). In addition, the volatility in both the soybeans and corn markets cause the volatility in the wheat market. In short, the volatility of biofuels (corn and soybeans) drives the feedstock (wheat) price volatility, while the energy is not similarly driven. The unidirectional relationship in the volatility values from the corn to the wheat market is in line with the results of Du et al. (2011), and the main reason for this relationship can be explained by the role of speculation. On the other hand, sugar markets are not related to the crude oil, soybeans, corn, and wheat markets. These results show that the price dynamics of the sugar markets is independent from the crude oil, soybeans, corn, and wheat markets and sugar markets have different, most likely local dynamics. This result is in line with the previous findings of Natalenov et al. (2013). In short, by the assumption that the price volatility in crude oil is the starting point of the transmission mechanisms, first, there is a spillover from the crude oil to the corn markets. Then, the corn market volatility interacts with the soybeans market, which is very likely due to the biofuel-related production, and their volatility dynamics both affect the wheat market as feedstock.

As noted by Andersen (2000) and Andersen et al. (2003), the volatility models that are based on price intervals in a trading day should be an advantage to understanding the nature of the price fluctuations. In similar, this paper presents a price volatility spillover analysis among the crude oil and the selected agricultural commodity markets. Actually, the use of biofuels as the corn ethanol by itself has substantially increased the price of corn, even with no change in the oil prices. An increase in the oil price will increase the price of corn and soybeans because the large scale production of each is currently impossible without the diesel fuel and gasoline. Therefore, the role of speculation appears to be prevalent in the futures trading. Our findings not only highlight the role of the biofuels production, but also refer to role of speculation to explain the volatility spillovers among the related markets.

Moreover, if the related data can be obtained, a further study can focus on the intraday data at a very high frequency (1, 5, 30 minutes of price data) to investigate the price volatility transmission mechanisms among the energy and agricultural commodity markets. This type of data set can also create a better understanding of the role of traders and speculations in the relationship between the energy and agricultural commodity markets, specifically in the financialization of commodities. Finally, using the intra-day data one can provide a volatility index that can be used to compare products.

Another alternative empirical strategy is that to use the residuals from other models, such as the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model, for a further investigation of causality. In this case, the approach of the Granger causality testing proposed by Bauer and Maynard (2012) would also be considered. We leave these issues to another study.

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