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Examining the Relationship of Crude Oil Future Price Return and Agricultural Future Price Return in US

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ABSTRACT

The purpose of this paper is to investigate the relationships between crude oil futures and agricultural grain commodities futures for soybeans, wheat and corn. Daily data for soybeans, wheat and corn are collected from Chicago Board of Trade and crude oil from New York Mercantile Exchange. The time period covered in this study extends from January 3, 2006 to February 22, 2012. In order to detect the relationships between crude oil and agriculture grain commodities futures, we apply the vector autoregression (VAR) model. From the VAR model, the change in each of agriculture grain commodities is significantly influenced by the change in the crude oil and other agriculture grain commodities.

Keywords: Crude Oil Futures, Agricultural Grain Commodities Futures, Granger Causality, Vector Autoregression
JEL Classifications: C58, G13, Q43, Q56

1. INTRODUCTION

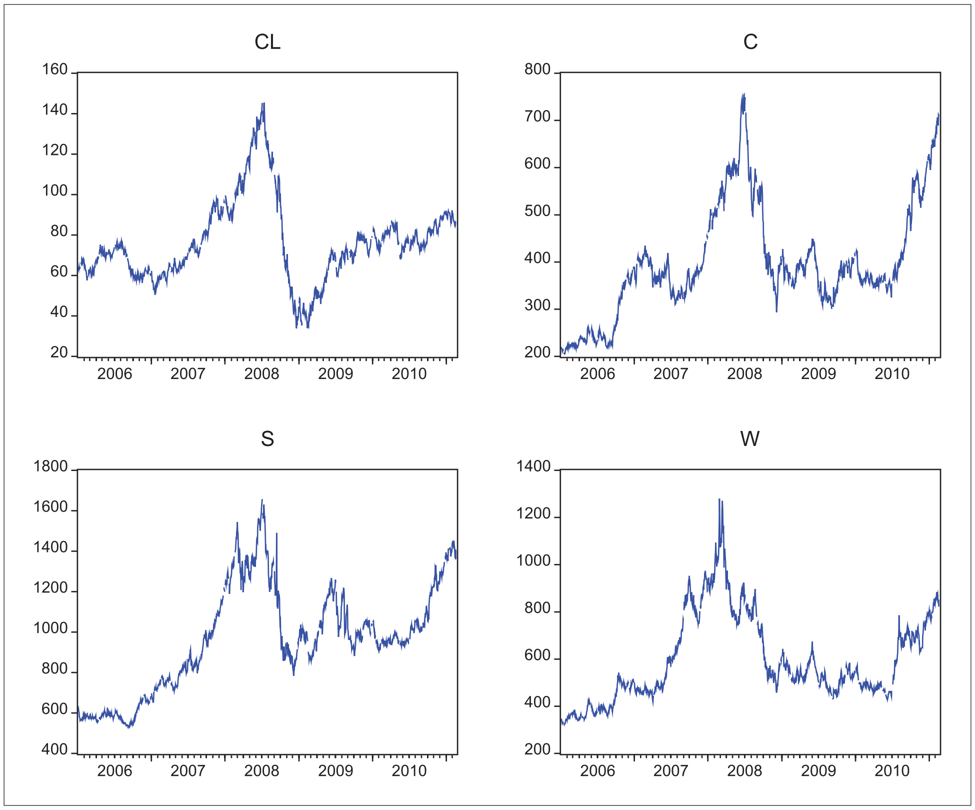
Volatility of prices for crude oil and oil products in general have increased during recent years. This contemporaneous increase in food and oil prices has reinforced attitudes towards the effect of oil prices on food prices. Figure 1 displays the crude oil and agricultural grain commodities prices during the period from January 3, 2006 to February 22, 2012, showing that there has been a significant relationship between the crude oil futures and agricultural grain commodities futures prices. Elobeid et al. (2007) pointed out that the ongoing growth of corn-based ethanol production, following the increase in the oil price, would have a significant impact on both US and world agriculture.

Rising oil price, limited supplies of fossil fuel and increased concerns about global warming have created a growing demand for renewable energy sources Srinivasan (2009). The production of these fuels is highly dependent on the availability of agricultural products. However, it is possible that biodiesel production could in fact cushion consumers from the negative effects of increasing world oil prices, but could result in increasing food prices.

In recent years, there is a significant increase in the production of bioenergy around the world, supported by the fact that many countries have set goals to replace a part of fossil fuels by biofuels. In the European Union, 5.75% of the energy used in transportation should be biofuels by the year 2010. By 2020, 10% of energy used in transportation should come from renewable energy source, particularly biofuels. The highest share of consuming biofuels in total transport fuels in 2007 was Brazil and US, 20% and 3% respectively. The major feedstocks currently used for biofuels production are directly or indirectly used for food production and there are claims that biofuels production significantly increases the prices of feedstocks and thereby of food. The major feedstocks for biofuels are soybeans, corn, wheat, and etc. Depending on climatic factors, the preferences for these feedstocks differ by regions. In US, bioethanol production is mostly based on corn. Biodiesel production in US is based on soybean oil, 82%. In EU-27, wheat is the major feedstock for bioethanol production. In 2008, 70% of total European bioethanol production was based on wheat and 10% corn. Biodiesel production in the EU is based on soybean oil, 18%.

Abbott et al. (2009) reduce the number of these factors to three key determinants: Excess demand, the value of US dollar, and the energy-agriculture linkage. However, the rise in energy prices is considered to

Figure 1: Plot of the light sweet crude oil futures (CLR), the soybeans futures (SR), the wheat futures (WR) and the corn futures (CR)



play the key role in explaining the recent dynamics of the agricultural commodity prices in the world. Energy and agricultural markets have become closely linked as production of biofuels has surged since 2006. Ethanol and biodiesel are substitutes for gasoline and diesel, leading to the recent surge in agricultural commodity prices as a result of increasing usage of crops in production of biofuels.

In this paper, we empirically assess the effect of crude oil future market on agricultural commodities futures market, for the January 2006 to February 2012 period. We examine how individual agricultural commodity futures return, rather than an aggregate index for the agricultural sector prices, is affected by changes in crude oil futures price. To that respect we employ a impulse responses to examine how each variable in the system responds to one standard deviation shock. The dynamic role means that short-run effects of external crude oil returns shocks on the agricultural commodity futures market can be different from long-run effects. Variance decomposition determines the extent to which the forecast error variance of each of the variable can be explained by shocks in the other variables.

The rest of this paper is organized as follows. The next section is devoted to the literature on the oil market-agricultural commodity market nexus. Estimation methodology is described in Section 3, followed by the data and empirical results in Section 4. The concluding remarks are presented in Section 5.

2. LITERATURE REVIEW

Gohin and Chantret (2010) investigate the long- run relationship between world prices of some food and energy products using a world computable general equilibrium model. They find a positive relationship due to the cost-push effect.

Chen et al. (2010) investigate the relationships between the crude oil price and the global grain prices of corn, soybean and wheat. The empirical results show that the change in each grain price is significantly influenced by the changes in crude oil price and other grain prices during the period extending from the 3rd week in 2005 to the 20th week in 2008, which implies that grain commodities are competing with the derived demand for bio-fuels using soybean or corn to produce ethanol or bio-diesel during the period of higher crude oil prices in these recent years.

Xiaodong and Hayes (2009) find evidence of volatility spillover among crude oil, corn and wheat markets, which could be largely explained by tightened interdependence between these markets induced by ethanol production. Alghalith (2010) estimate the impact of oil price uncertainty on food prices. The empirical results indicate that a higher oil price increases food price. Also, a higher oil price volatility yields a higher food price. Moreover, an increase in the oil supply reduces the food price.

William (2008) and Rosegrant (2008) indicated that using crops for fuel is the driving factor for an increase of food prices. The food price increase in the last few years has been mainly explained as a result of the expansion of biofuels, which reduced the availability of food supply at the international market and increased food prices.

Tokgoz and Elobeid (2006) investigated how price changes in the petroleum, corn, and sugar markets might affect the bioethanol and related agricultural markets in the US and Brazil. They concluded that the biofuel vehicle type (e.g., gasohol, ethanol, and flexible fuel) could affect the direction of the response of ethanol consumption to gasoline price change.

Zhang and Reed (2008) examine the impacts of world crude oil prices on China's corn, soy meal, and pork prices for period January 2000-October 2007. By applying a VARMA model, Granger causality test, impulse response functions, variance decomposition, and cointegration analysis, authors conclude that the world crude oil prices are not a major factor contributing to the recent soaring in the selected agricultural prices of China.

Urbanchuk (2007) found that rising oil and energy prices had twice the impact on food prices as measured by the Consumer Price Index than did ethanol production and the price of corn. Kind et al. (2009) have similarly finding. They found that the growing use of corn for ethanol accounted for about 10-15% of the increase in the food prices over the period of April 2007-2008.

Zhang et al. (2009) studied relationships between price levels within this industry using cointegration techniques and vector error correction models (VECM). Price volatility interactions were also modeled by means of a multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model. SVAR, cointegration, VECM, and MGARCH models all belong to the category of "linear" models in the sense that they do not allow for changing price behavior that depends on the predominant economic conditions.

Serra et al. (2011) assesses volatility interactions within the Brazilian ethanol markets by using a parametric approach to estimate MGARCH models based on Seo (2007). They find important volatility spillovers across markets that flow in multiple directions.

Natanelov et al. (2011) focus on price movements between crude oil futures and a series of agricultural commodities and gold futures. Their results indicate that co-movement is a dynamic concept and that some economic and policy development may change the relationship between commodities.

Zhang and Qu (2015) studied the effect of global oil price shocks on agricultural commodities in China, including strong wheat, corn, soybean, bean pulp, cotton and natural rubber. Empirical results found that the oil price was characterized by volatility clustering and jump behavior. At the same time, oil price shocks had different effects on agricultural commodities. In addition, the shocks on most agricultural commodities were asymmetric.

3. METHODOLOGY

Since many of the financial variables are in non-stationary time series, we employed the ADF test (Dickey and Fuller, 1981) for our variables prior to constructing the VAR model (Sims, 1980). In non-stationary time series, this method is common for first identifying the difference in the variables. In stationary time series, the ADF unit root test is employed first, followed by the VAR model has been proven especially useful for describing the dynamic behavior of economic and financial time series.

3.1. Vector Autoregression (VAR)

Theoretical findings from the previous section suggest that the oil prices affect agricultural commodity prices and, to a lesser extent, oil price may affect agricultural commodity prices. Hence, both oil and agricultural commodity prices are endogenous. In standard regression models by placing particular variables on the right hand side, the endogeneity of all variables sharply violates the exogeneity assumption, of a regression equation. This problem can be circumvented by specifying a VAR model on a system of variables, because in VAR no such conditional factorization is made a priori. Instead, variables can be tested for exogeneity later, and restricted to be exogenous then. These considerations motivate our choice of the VAR model for studying the interdependencies between the crude oil and agricultural grain commodities returns series.

Both impulse response functions and variance decomposition are obtained from the same VAR system. Impulse response functions describe the dynamic response of dependent variables to a one-period shock and another exogenous variable. Variance decomposition functions demonstrate how each of the considered exogenous variables contributes to the changes in dependent variables. Variance decomposition analysis divides the forecast error variance of dependent variables into proportions attributable to shocks in other exogenous variables.

Stationary processes, which have time invariant expected values, variances, and co-variances, i.e., the first and second moments of the random variables do not change over time, can be analysed using a simple VAR model. The m-variable VAR model of order n can be written as:

$$Y_t = A_0 + \sum_{i=1}^{n} A_i Y_{t-1} + \varepsilon_t \qquad (1.1)$$

Where Y_t is a $M \times 1$ vector of oil and agricultural commodities returns series at time t, A_0 is a $M \times 1$ vector of constants, A_i is a $M \times M$ matrix of coefficients relating series changes at lagged i period to current changes in series, and ε_t is a $M \times 1$ vector of IId errors. According to VAR model, each of the M variables is a function of n lags of all M variables, including itself, a constant and a contemporaneous error term.

3.2. Impulse Response Function

Rewriting the Equation 1.1 as representation vector moving average (VMA),

$$Y_t = \mu + \sum_{i=1}^{\infty} \Phi_i + \varepsilon_{t-1} \qquad (1.2)$$

Where Φ_i is a $m \times m$ matrix with elements $\Phi_{ik}(i)$. The $\Phi_{ik}(i)$ are coefficients of ε_{t-1} with respect to the shocks of ε_{t-1} on the endogenous variable j. Hence, the sets of coefficients $\Phi_{jk}(i)$ are the impulse response of the dependent variable due to the shock in each explanatory variable's error term.

3.3. Variance Decomposition

Given Equation 1.1, the conditional expectation of Y_{t+1} is $A_0+A_1Y_1$ and the one-step-ahead forecast error is $Y_{t+1}=E_t(Y_{t+1})=e_{t+1}$, while the two-step-ahead forecast error is $A_1e_{t+1}+e_{t+2}$. Hence, the n-step-ahead forecast error is

$$Y_{t+n}=E_t\left(Y_{t+n}\right)=e_{t+n}+A_1Y_{t+n-1}+A_1{}^2Y_{t+n-2}+\ldots+A_1{}^{n-1}Y_{t+1}$$
$$=\sum_{i-0}^{n-1}A_1{}^i e_{t+n-i} \tag{1.3}$$

Which equals to

$$\sum_{i=0}^{n-1}\Psi_i\varepsilon_{t+n-i} \tag{1.4}$$

Derived from Y_t in a VMA representation. Equations 1.3 and 1.4 provide the exact information in explaining the forecast error in different forms. Using the equation to denote the variance of the n-step-ahead forecast error variance of each variable in the explicit form, the n-step forecast error variance could be decomposed through each one of the shocks.

4. DATA AND EMPIRICAL RESULTS

4.1. Data Summary

The time period covered in this study extends from January 3, 2006 to February 22, 2012. The Daily price data for soybeans, wheat and corn are obtained from the futures contracts traded on the Chicago Board of Trade and the crude oil price is the light sweet crude oil future contracts traded on the New York Mercantile Exchange. The data set was subsequently transformed into daily returns, with the returns defined in their logarithmic form as: $R_t = \ln(P_t/P_{t-1})$, where R_t and P_t are the return in percent and the commodity closing price on day(t), respectively. The following notations will be employed in the rest of the paper: The returns of the light sweet crude oil future (CLR), soybeans future (SR), wheat future (WR) and corn future (CR). Table 1 provides the descriptive statistics for the sample means, standard deviations, skewness, kurtosis, and the JB statistics of the four return series. From the sample statistics, the skewness and kurtosis coefficients show that the oil and corn returns are skewed right with a fat-tailed distribution, but the soybeans and wheat returns are skewed left with a fat-tailed distribution. The Jarque-Bera statistic shows that the null hypothesis of normality is rejected at the 1% level of significance.

Table 1: Descriptive statistics

	CLR	SR	WR	CR
Mean	0.0003	0.0006	0.0006	0.0009
Maximum	0.1641	0.2032	0.0898	0.1276
Minimum	−0.1307	−0.2341	−0.0997	−0.0810
Standard deviation	0.0268	0.0206	0.0249	0.0225
Skewness	0.0887	−0.8414	−0.0277	0.0426
Kurtosis	7.1107	24.3482	4.1475	4.6285
JB statistic	890.0779***	21849.69***	70.74048***	142.7460***

JB statistic is used for normal distribution test. L-BQ(x) and L-BQ²(x) are the Ljung-Box statistics for the level and squared term for the autocorrelations up to x lags. ***,**,*Denote statistical significance at 1%, 5%, 10% levels. JB: Jarque-Bera, CLR: Crude oil future, SR: Soybeans future, WR: Wheat future, CR: Corn future

4.2. Augmented Dickey–Fuller (ADF) Test

Before testing correlations and causality among the four variables, we must confirm that all the series are stationary and integrated of the same order. Based on the ADF tests on the individual series (Dickey and Fuller, 1979), the optimal lagged period can be acquired with the least AIC value, which can be used for ADF test approach. The ADF unit root tests support the rejection of the null hypothesis of a unit root at the 1% significance level, implying that the four return series are stationary and may be modeled directly without any further transformation.

4.3. VAR

4.3.1. Impulse response analysis

The estimated impulse response of the VAR system enables us to examine how each of the four variables responds to innovations from other variables in the system and the functions can be used to produce the time path of the dependent variables in the VAR, to shocks from all the explanatory variables. A stable system of equations should cause any shock to decline to zero while an unstable one would produce an explosive time path. This makes it possible to compare the prediction of the model with those of economic theory.

We now present the impulse responses of soybeans futures returns (SR), wheat futures returns (WR) and corn futures returns (CR) to the crude oil futures returns (CLR) shock, defined as one standard deviation (SD) of the crude oil futures returns. With regards to the crude oil futures returns shocks presented in Figure 2, the initial response of soybeans futures returns, wheat futures returns and corn futures returns are positive and significant. These impacts vanish quickly by the second horizon (day) in the case of CLR as the SR, WR and CR return rapidly to its steady state level. On the contrary, the return of soybeans futures, wheat futures and corn futures has no impact on crude oil futures. The initial response of crude oil is not significant and dies away throughout the twenty periods. Hence, we find that a shock in oil returns has a powerful influence on agricultural grain market.

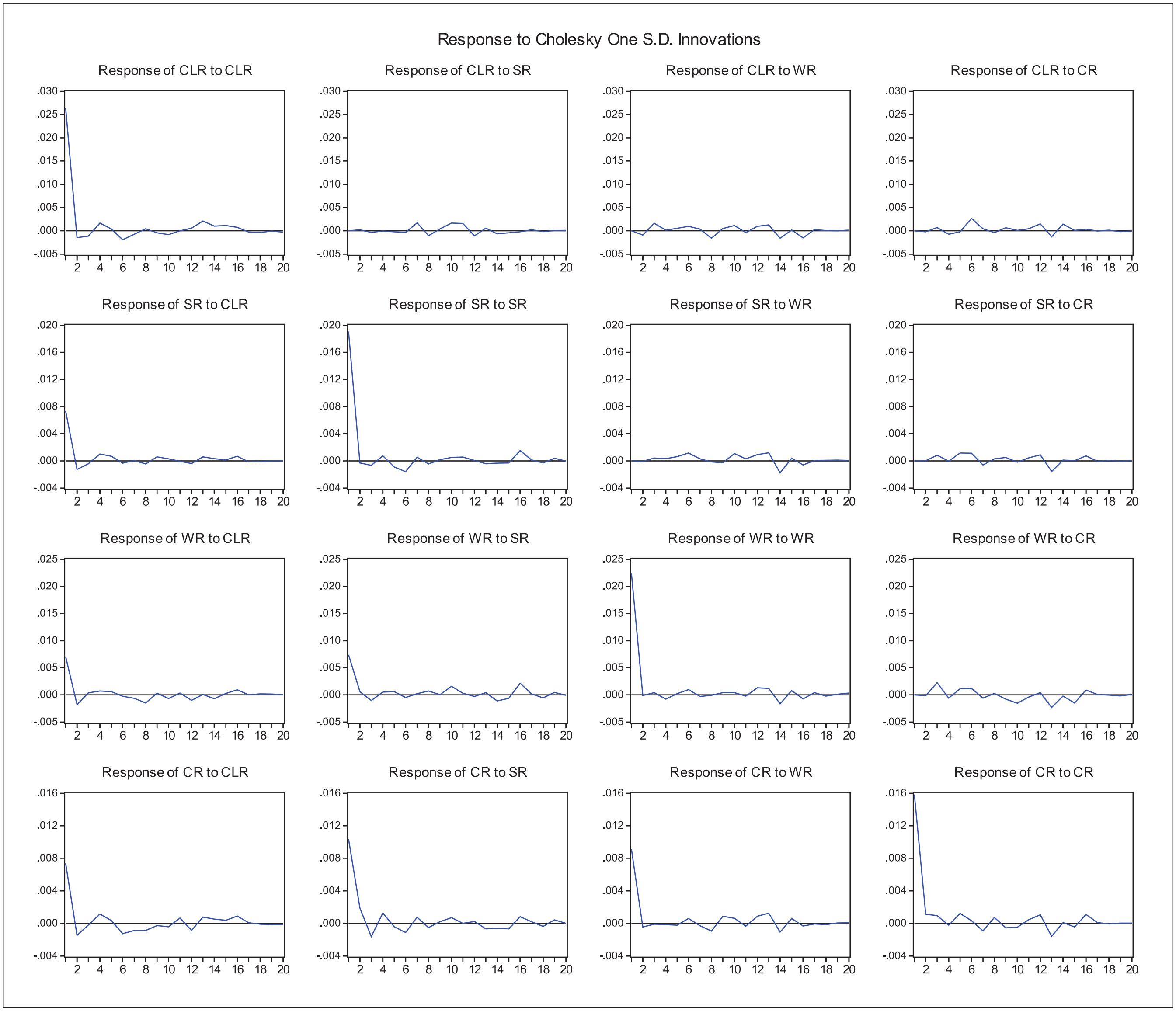
The corn futures returns initially responds positively to shocks in soybeans futures returns and its initial impact on the wheat futures returns of shock in soybeans future returns is also positive and significant. However, it is noticeable that a shock in soybeans futures returns has a relatively major impact on corn market, compared to wheat market.

The initial impacts of crude oil futures returns, soybeans futures returns and wheat futures returns on corn futures returns are positive and significant as well, but disappear quickly by the second period in the case of CLR, SR and WR as the CR returns rapidly to its steady state level.

4.3.2. Variance decomposition

This is an alternative method to the impulse response functions for examining the effects of shocks to the dependent variables, a technique which determines how much of the forecasting error variance for any variable in a system can be explained by

Figure 2: The impulse-responses of the returns of the light sweet crude oil future (CLR), soybeans future (SR), wheat future (WR) and corn future (CR)



innovations of each explanatory variable over a series of time horizons. Usually, shocks in the series explain most of the error variances, although the shock will also affect other variables in the system. It is also important to consider the order of the variables when these tests are conducted, because in practice the error terms of the equations in the VAR will be correlated, leading to the fact that result will be dependent on the order in which the equations are estimated in the model.

Here, variance decomposition indicates the amount of information that each variable contributes to the other variables in a VAR models. A variance decomposition analysis of this full VAR version for forecasting horizons from 1 to 20 days is presented in Tables 1 and 2. The numbers in the Tables 1 and 2 report the percentage of the forecasting error in each variable that we can attribute to each of the structural innovations at different horizons.

The results clearly suggest that most of the volatility in all variables can be explained by own shocks. The accountability of soybeans, wheat and corn returns on the forecasting error of oil returns varies from 0.00% in short horizon to 1.55%, 2.17%, and 2.02% in longer horizon, respectively. Oil returns are little affected in all horizons. The percentage of the error variance accounted for by its own shock is approximately 100% in the short run. A one standard deviation shock to the oil returns has impacts of approximately 13.18%, 9.12%, and 12.04% on soybeans, wheat and corn returns in the long run, respectively,

Table 2: Results for unit root tests

	ADF	
	C	C&T
CLR	−16.6514 (4)***	−16.6448(4)***
SR	−17.3436(4)***	−17.3391(4)***
WR	−36.5860(0)***	−36.5763(0)***
CR	−34.7457(0)***	−34.7319(0)***

ADF tests with constant (level); C - constant; T - trend. Superscripts ***,**,*Denote rejection of the null hypothesis of a unit root at 1%, 5%, 10% level of significance. ADF: Augmented Dickey-Fuller, CLR: Crude oil future, SR: Soybeans future, WR: Wheat future, CR: Corn future suggesting that there is a relationship between oil returns and agriculture commodity returns.

The SR explains 87.06% of the forecasting error variance for the change in SR in the first period while the explaining power drops to 82.94% at the 20th day forecasting horizons. Although the impact of soybeans returns on oil returns is insignificant in magnitude, the impacts of wheat and corn returns areapproximately 10.25% and 22.41%, respectively. The WR explains 82.69% of the forecasting error variance for the change in WR in the first period and the accountability of wheat returns on the forecasting error of corn returns is 16.74%. The CR explains 50.60% of the forecasting error variance for the change in CR in the first period with the impacts of corn future returns on other agricultural grain commodities future returns remaining insignificant in magnitude (Table 3).

In each case, on the one hand, we find the shocks in crude oil returns play a relative key role in soybeans, wheat and corn futures returns. On the other hand, the shocks in the agricultural grain commodities futures market do not clarify a significant proportion of variation for crude oil futures market. For crude oil, nearly all of the variance decomposition results from movements, implying that oil price movements can influence soybeans, wheat and corn futures returns, but not *vice versa* (Table 4).

Table 3: The variance decomposition tests of CLR return and SR return

Variance decomposition of CLR						Variance decomposition of SR					
Period	SE	CLR	SR	WR	CR	Period	SE	CLR	SR	WR	CR
1	0.0264	100.0000	0.0000	0.0000	0.0000	1	0.0205	12.9423	87.0577	0.0000	0.0000
2	0.0265	99.8633	0.0074	0.1210	0.0084	2	0.0205	13.2638	86.7352	0.0009	0.0002
3	0.0266	99.4033	0.0243	0.4928	0.0795	3	0.0205	13.2616	86.5335	0.0404	0.1645
4	0.0266	99.3265	0.0247	0.4934	0.1554	4	0.0206	13.4508	86.3189	0.0662	0.1640
5	0.066	99.2758	0.0329	0.5304	0.1609	5	0.0206	13.4624	85.9062	0.1584	0.4731
6	0.0269	98.1618	0.0498	0.6441	1.1443	6	0.0208	13.3210	85.4425	0.4666	0.7700
7	0.0269	97.7382	0.4443	0.6553	1.1622	7	0.0208	13.2996	85.3667	0.4844	0.8493
8	0.0270	97.2319	0.5902	1.0018	1.1761	8	0.0208	13.3307	85.3128	0.4897	0.8669
9	0.0270	97.1265	0.6095	1.0301	1.2340	9	0.0208	13.3881	85.1801	0.5079	0.9240
10	0.0271	96.6099	0.9711	1.1920	1.2271	10	0.0209	13.3612	84.9451	0.7655	0.9281
11	0.0272	96.2451	1.2979	1.2085	1.2485	11	0.0209	13.3437	84.8996	0.7840	0.9724
12	0.0272	95.6863	1.4523	1.3230	1.5383	12	0.0209	13.3257	84.5499	0.9750	1.1494
13	0.0274	95.2666	1.4772	1.5179	1.7383	13	0.02101	13.2705	83.7540	1.2866	1.6889
14	0.0275	94.6158	1.5226	1.8566	2.0050	14	0.0211	13.1952	83.1513	1.9740	1.6794
15	0.0275	94.5941	1.5469	1.8569	2.0021	15	0.02110	13.1921	83.1245	2.0048	1.6786
16	0.0276	94.2799	1.5459	2.1641	2.0101	16	0.0212	13.1851	82.9573	2.0693	1.7883
17	0.0276	94.2671	1.5507	2.1723	2.0099	17	0.0212	13.1899	82.9519	2.0695	1.7887
18	0.0276	94.2629	1.5536	2.1718	2.0117	18	0.0212	13.1888	82.9520	2.0703	1.7889
19	0.0276	94.2585	1.5539	2.1717	2.0159	19	0.0212	13.1840	82.9548	2.0724	1.7888
20	0.0276	94.2563	1.5543	2.1734	2.0160	20	0.0212	13.1839	82.9540	2.0731	1.7890

SE: Standard error, CLR: Crude oil future, SR: Soybeans future, WR: Wheat future, CR: Corn future

Table 4: The variance decomposition tests of WR return and CR return

Variance decomposition of WR						Variance decomposition of CR					
Period	SE	CLR	SR	WR	CR	Period	SE	CLR	SR	WR	CR
1	0.0246	8.2165	9.0907	82.6928	0.0000	1	0.0223	10.9901	21.6684	16.7444	50.5971
2	0.0247	8.7097	9.0948	82.1919	0.0037	2	0.0224	11.2680	22.0569	16.5450	50.1301
3	0.0248	8.6433	9.1858	81.3642	0.8067	3	0.0225	11.1976	22.4118	16.4306	49.9601
4	0.0248	8.7027	9.2001	81.2326	0.8645	4	0.0226	11.3912	22.5977	16.3376	49.6735
5	0.0249	8.7302	9.2238	80.9779	1.0681	5	0.0226	11.3727	22.5510	16.2874	49.7888
6	0.0249	8.7044	9.2246	80.7804	1.2907	6	0.0227	11.6171	22.6464	16.2513	49.4851
7	0.0249	8.7563	9.2185	80.6765	1.3488	7	0.0227	11.7126	22.6565	16.1994	49.4315
8	0.0250	9.0798	9.2583	80.3098	1.3521	8	0.0228	11.8010	22.6013	16.2938	49.3039
9	0.0250	9.0804	9.2454	80.2234	1.4509	9	0.0228	11.7880	22.5579	16.4057	49.2483
10	0.0251	9.0754	9.5512	79.5572	1.8162	10	0.0228	11.7938	22.5945	16.4416	49.1701
11	0.0251	9.0846	9.5596	79.5114	1.8443	11	0.0229	11.8556	22.5628	16.4409	49.1407
12	0.0252	9.1996	9.5292	79.4085	1.8627	12	0.0229	11.9428	22.4589	16.4999	49.0984
13	0.0253	9.1001	9.4519	78.7658	2.6822	13	0.0230	11.9420	22.3275	16.6311	49.0994
14	0.0254	9.1172	9.5844	78.6269	2.6715	14	0.0231	11.9547	22.3185	16.7906	48.9363
15	0.0255	9.0809	9.6011	78.3176	3.0004	15	0.0231	11.9571	22.3529	16.8205	48.8695
16	0.0256	9.1217	10.1811	77.6045	3.0927	16	0.0232	12.0451	22.3615	16.7519	48.8415
17	0.0256	9.1187	10.1829	77.6061	3.0923	17	0.0232	12.0448	22.3662	16.7510	48.8381
18	0.0256	9.1184	10.2264	77.5648	3.0905	18	0.0232	12.0422	22.3860	16.7498	48.8220
19	0.0256	9.1172	10.2523	77.5351	3.0954	19	0.0232	12.0411	22.4113	16.7440	48.8036
20	0.0256	9.1158	10.2512	77.5374	3.0956	20	0.0232	12.0441	22.4103	16.7444	48.8013

SE: Standard error, CLR: Crude oil future, SR: Soybeans future, WR: Wheat future, CR: Corn future

5. CONCLUSION

The prices of crude oil and agriculture grain products have followed similar patterns with large fluctuations in recent years. The major purpose of this paper is to investigate the relationships among the crude oil returns, and the returns of soybeans, wheat and corn over the period from January 3, 2006 to February 22, 2011. We investigate the relationship between these returns using VAR model with detailed representations of crude oil and agriculture grain commodities markets.

The impulse response analysis results suggest that all agricultural commodities returns are affected by crude oil returns. The impact of a positive oil market shock on agricultural commodities is considerably larger than vice versa. A one standard deviation shock to the oil returns has an approximately 13.18%, 9.12%, and 12.04% impact on soybeans, wheat and corn returns in the long run, respectively. The results suggest that there is a relationship between oil returns and agriculture commodity returns.

This finding is consistent with the observation that grain commodities are competing with the derived demand for biofuels by using soybeans to produce biodiesel, wheat and corn to produce bioethanol in these recent years. The shock steadily raised biofuels demand for soybeans, wheat and corn as an alternative fuel for petroleum, which in turn increased agricultural prices in the short term. In addition, because there was a limited endowment of planted acreage and other grains were increasingly being used as substitutes for corn, the prices of wheat and other alternative grain prices also surged to high levels. This suggests that the crude oil price is the important factor of production cost for grain commodities and intensifies the competition relationships between alternative agriculture grains.

REFERENCES

Abbott, P.C., Hurt, C., Tyner, W.E. (2009), What's driving food prices? Farm Foundation Issue Report. March, 2009 Update.

Alghalith, M. (2010), The interaction between food prices and oil prices. Energy Economics, 32, 1520-1522.

Chen, S.T., Kuo, H.I., Chen, C.C. (2010), Modeling the relationship between the oil price and global food prices. Applied Energy, 87, 2517-2525.

Ciaian, P., Kancs, D. (2011), Interdependencies in the energy-bioenergy-food price systems: A cointegration analysis. Resource and Energy Economics, 33, 326-348.

Elobeid, A., Tokgoz, S., Hayes, D., Babcock, B., Hart, C. (2007), The long-run impact of corn-based ethanol on the grain, oilseed, and livestock sectors with implications for biotech crops. AgBioForum, 10, 8-11.

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

Kind, R., Rosa, D., James, M. (2009), Implications of ethanol use for food prices and greenhouse-gas emissions. Congressional Budget Office.

Natanelov, V., Alam, M.J., Mckenzie, A.M., Huylenbrock, G.V. (2011), Is there co-movement of agricultural commodities future prices and crude oil? Energy Policy, 4971-4984.

Rosegrant, M. (2008), Biofuels and grain prices: Impacts and policy responses. Testimony for the US Senate Committee on Homeland Security and Governmental Affairs. Washington, DC: International Food Policy Research Institute. Available from: http://www.ifpril.org.

Serra, T., Zilberman, D., Gil, J.M. (2010), Price volatility in ethanol markets. European Review of Agricultural Economics, 41, 1-22.

Srinivasan, S. (2009), The food v. fuel debate: A nuanced view of incentive structures. Renewable Energy, 34, 950-954.

Tokgoz, S., Elobeid, A. (2006), An analysis of the link between ethanol, energy, and crop markets. Working Paper 06-WP 435, CARD, Iowa State University.

Urbanchuk, J. (2007), The relative impact of corn and energy prices in the grocery Aisle. Available from: http://www.lecg.com.

William, E. (2008), World Bank Secret report confirms biofuels cause of world food crisis. Global Research. Available from: http://www.globalresearch.ca/PrintArticle.php? articleId¼9547.

Xiaodong, D., Hayes, D. (2009), The impact of ethanol production on us and regional gasoline markets. Energy Policy, 37, 3227-3234.

Zhang, C., Qu, X. (2015), The effect of global oil price shocks on China's agricultural commodities. Energy Economics, 51, 354-364.

Zhang, Q., Reed, M. (2008), Examining the Impact of the World Crude Oil Price on China's Agricultural Commodity Prices: The Case of Corn, Soybean, and Pork. The Southern Agricultural Economics Association Annual Meetings, Dallas, TX. February 2-5, 2008.

Zhang, Z., Lohr, L., Escalante, C., Wetzstein, M. (2009), Ethanol, corn, and soybean price relations in a volatile vehicle-fuels market. Energies, 2, 320-339.