Cointegration and Causality Analysis of World Vegetable Oil and Crude Oil Prices

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May 31, 2006

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Long Beach, California July 23-26, 2006

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Abstract

Because of the recent soaring petroleum price and growing environmental concerns, biodiesel has become an important alternative fuel. Biodiesel is the mono alky esters made from a vegetable oil, such as soybean or rapeseed oil, or sometimes from animal fats. The escalation in world petroleum price has stimulated the demand for biodiesel, which consequently expanded the use of vegetable oils. This paper investigates the long-run interdependence between major edible oil prices and examines the dynamic relationship between vegetable and crude oil prices. The data consists of 378 weekly observations extending from the first week of January in 1999 to the fourth week of March in 2006. We apply time-series analytical mechanisms and directed acyclic graphs to four major traded edible oils prices, including soybean, sunflower, rapeseed and palm oils, along with one weighted average world crude oil price. Tentative results suggest one long-run cointegration relationship among those five oil prices. Also, the edible oil markets are well linked in contemporaneous time with the palm oil market initiating the new information; however, soybean oil price dominates the edible oil markets in the long run. The influence of crude oil price on edible oil prices is not significant over the study period.

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The international market for edible oils is expanding at a significant pace because of the rapid growth in world population and income. In 1994/95, the world production of the primary vegetable oils was about 73 million tons; however, by 2003/04 production had increased by 47 percent to 107 million tons (ISAT Mielke GmbH). During this same time period, world trade in edible oil increased about 66 percent. This increase in production and trade reflects the surging global demand for vegetable oils. In general, vegetable oils are demanded for margarine, cooking oil and compound fats. Some vegetable oils also have industrial uses, such as soap making or biodiesel. Because of the recent soaring petroleum price and growing environmental concerns, biodiesel has become an important alternative fuel. The world production of biodiesel increased from about 0.6 billion liters in 1998 to 1.8 billion liters in 2003 and it continues to expand rapidly (F.O. Lichts). Biodiesel is a mono alky ester that is made from a vegetable oil, such as soybean or rapeseed oil, or sometimes from animal fats. The escalation in world crude oil price has stimulated the demand for biodiesel, which consequently expanded the use of vegetable oils. Currently, the primary production of biodiesel is concentrated in Europe with rapeseed oil as the major source. In Brazil and U.S., biodiesel production has increased considerably with soybean oil as the major input; however, in Malaysia, palm oil is used in biodiesel production.

The market prices of vegetable oils are presumably interacting with each other and with crude oil prices, since there is a considerable degree of substitutability among selected vegetable oils, and high world crude oil price has prompted the use of vegetable oils as a fuel. Several previous studies have attempted to measure the interdependence among vegetable oil prices with annual or monthly data and generally researchers have found similar price patterns for evaluated prices (Duncker; In and Inder; Griffith and Meilke; Labys; Owen, Chowdhury, and Garrido). However, some studies have obtained variant outcomes regarding the long-run relationship among selected vegetable oil prices. For example, Owen, Chowdhury and Garrido found no evidence of cointegration among the five major internationally traded vegetable oils over the 1971 to 1993 period. However, using similar vegetable oil prices and study period, In and Inder observed a long-run co-movement relationship among edible oil prices.

In this study, we investigate the long-run interdependence between major edible oil prices and examine the dynamic relationship between vegetable and crude oil prices with weekly data. The objective of this paper is to gain better insight of interacting price behavior among edible oil prices using less time aggregated data than previous studies; furthermore, we intend to develop a fundamental understanding of the likely affiliation between vegetable and crude oil prices. For instance, is there a long-run relationship between edible oils and crude oil prices? What is the impact of a volatile crude oil price on the world vegetable oil prices? How much does the volatility of the crude oil price affect forecast variation in the world edible oil prices? This information is of particular importance, as increasing numbers of countries attempt to find alternative fuels for petroleum to reduce their dependence on a non-renewable energy sources and alleviate environmental pollution. This study into the dynamic interrelationship between crude and vegetable oil prices may help producers and traders of oilseeds and vegetable oils to plan their business operations and provide government with information regarding policy formulation.

The remainder of the paper is structured as follows: The second section discusses the method of analysis in this paper. Data and variables will be presented in the third section, while section four will discuss the empirical results. The concluding remarks will be offered in the last section.

Method of Analysis

To explore the dynamic interdependence among edible and crude oils markets, a multivariate time-series model is employed in this study. In addition, a graphical modeling analysis, directed acyclic graphs, is adopted to determine the contemporaneous relationships among these markets.

Multivariate Time-Series Model

Generally, vector autoregressive (VAR) models are tools for analyzing a set of interrelated variables. An m-variable VAR model of order n is written as:

$$(1) \qquad P_t = \sum_{i=1}^{n} \Gamma_i P_{t-i} + \mu + e_t$$

where *P* is a (Mx1) vector of series at time t, Γ_i a (MxM) matrix of coefficients relating series changes at lagged *i* period to current changes in series, μ is a (Mx1) vector of constants, and ε_t is a (Mx1) vector of independent identically-distributed (i.i.d.) errors. Equation (1) indicates that each of the M variables is a function of *n* lags of all M variables, including itself, a constant and a present innovation (error) term. If some series in the set of evaluated variables are non-stationary and cointegrated, a pure VAR in differenced data will be mis-specified (Engle and Grnger). Under this circumstance, the error correction model (ECM), developed by Johansen (Johansen, 1988, 1991; Johansen and Juselius, 1990), will be appropriate to study both short-run discrepancies and long-run equilibrium. An ECM model is written as follows:

$$(2) \qquad \Delta P_t = \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + \Pi P_{t-1} + \mu + e_t (t = 1,...,T)$$

Clearly, equation (2) is a VAR model in first differences plus a lagged-level term. The P_{t-1} is the so-called Error Correction Term and the Π is a (MxM) coefficient matrix containing response information of lagged levels of price/rates to current changes.

The long run, short run and contemporary information among those series can be identified through the parameters in equation (2). The information on long-run relationship between the M variables is summarized in Π. When the rank of Π is a positive number, *r*, and it is less than the number of series, *M*, then $\pi = \alpha\beta'$ where α and β are (M x r) matrices. The β matrix contains the cointegrating parameters and the matrix α includes the information on the speed of adjustment. Testing hypotheses on β can provide information on long-run structure, while testing hypotheses on α and Γ_i can identify the short-run relationships (Johansen and Juselius, 1994; Johansen, 1995). Furthermore, the contemporaneous structure can be summarized through structural analysis of e_t, as described recently in Bessler and Lee (2002) and Demiralp and Hoover (2003).

The information on the contemporaneous structure of interdependence may be explored by examining the causal relationship among innovations in contemporaneous time *t*, across markets based on the variance-covariance matrix of innovations (i.e., residuals) from the ECM (Spirtes, Glymour, and Scheines, 2000). Directed acyclic graphs, a graphical modeling methodology, offers help in providing data-based evidence of ordering in contemporaneous time *t*, assuming the information set on Σ_t is causally sufficient. A Bernanke ordering may be used with the structure found with the directed graphs on contemporaneous structure (Bernanke, 1983; Doan, 1992).

Directed Acyclic Graphs

The directed acyclic graphs methodology employed here emanates from the field of artificial intelligence and computer science (Pearl, 2000). A directed graph is a picture representing causal flows among variables that have been suggested by prior study or theory to be related. The basic idea is to represent causal relationships among a set of variables using an arrow graph or picture. Mathematically, directed graphs are designs for representing conditional independence as implied by the recursive product decomposition:

$$(3) \qquad \Pr(y_1, y_2, y_3, \ldots, y_m) = \prod_{i=1}^{m} \Pr(y_i \mid v_i)$$

where *Pr* is the probability of variables y_1 , y_2 , …, y_m; while v_i, presents a subset of variables with y_i in order (i = 1, 2, …, m). Pearl (1986, 1995) illustrated the independence relations given by equation (3) by introducing *d-separation*. When the information is blocked between two vertices (say A and B), the two are *d-separated*. This can be found in three cases: a) condition a mediator is causal chains, say B in the graph A → B → C; b) condition a common cause in a causal forks, say variable Z in the graph X ← Z → Y; or c) *do not* condition on a middle variable, say E or any of its descendents in the graph of D→E←F (descendents are not presented here).

Our analysis is based on the idea that causal chains (A→ B→C), causal forks (A←B→C), and causal inverted forks (A→B←C) imply particular correlation and partial correlation structures between and among the measures A, B, and C (Geiger, Verma, and Pearl). If A, B, and C are related as a chain (A→ B→C), the unconditional correlation between A and C will be non-zero. However, the conditional correlation between A and C given the information in B will be zero. If the three variables A, B, and C are instead related as an inverted fork

(A→B←C), then the unconditional correlation between A and C will be zero, but the conditional correlation between A and C, given B, will be nonzero. Finally, if the events are related in a causal fork (A←B→C), the unconditional correlation between A and C will be non-zero, but the conditional correlation between A and C given B will be zero.

Greedy equivalence search (GES) algorithm is utilized to identify the contemporaneous structure. The GES algorithm searches in a stepwise manner using a Bayesian scoring criterion to score all possible causal flows between variables to obtain the "best" graph. This algorithm is described in Chickering (2002). The software TETRAD IV is employed to process the GES algorithm and its extensions.

Data and Variables

Since this study is designed to explore the interactions between edible and crude oil prices, we select edible oils used in the production of biodiesel. In 2002, rapeseed was the dominant source of biodiesel production (84%), followed by sunflower oil (13%), soybean oil (1%), palm oil (1%) and others (1%) (Pahl). Therefore, four world vegetable oils prices, including soybean, rapeseed, sunflower and palm oil, along with a world crude oil price are analyzed. The four edible oils are also the major internationally traded oils, accounting for about 86 percent of total world vegetable oil imports in 2003/04 (ISAT Mielke GmbH). All the vegetable oil prices used in this study are border prices, i.e. free on board (f.o.b.) or cost, insurance and freight (c.i.f.) prices. In addition, the prices are from markets located in major world edible oil trade centers, such as Rotterdam, therefore, they represent a world price. The prices were provided by ISTA Mielke GmbH, in Hamburg, Germany and are in US$ per ton. Undoubtedly, these prices will reflect strengthening/weakening in the U.S. dollar; however, this study is primarily focusing on the relative movements in prices so this is not a concern.

For crude oil, we select the average spot f.o.b. price of all countries weighted by estimated export volume, taken from the U.S. Department of Energy, Energy Information Administration. Both vegetable oils and crude oil prices are weekly data extending from the first week of January in 1999 to the fourth week of March, 2006. Table 1 presents the statistical summary of the five oil prices while Figure 1 shows the five oil prices over the study period. The four edible oil prices move together, except the rapeseed oil price which is stronger in latter periods. The crude oil price is stable in early periods but starts climbing in mid-2003. Generally, the relationship between edible and crude oil prices in Figure1 is not strong.

In addition to the price series, several dummy variables were generated to capture the potential influence of policies and structural changes in the industry over the study period. A binary dummy variable was created regarding the U.S. and Iraq war on March 20 in 2003; with 0 for the period prior to the war and 1 afterwards. It is believed the war has a considerable impact on crude oil prices. Also, the European Commission adopted the Directive for Promotion for biodiesel on May 14, 2003, which requires an expansion in biofuels' market share to 2 percent by 2005 and 5.75 percent by 2010. A binary dummy variable was generated with respect to this policy since it presumably manipulates the vegetable oil market. Finally, eleven monthly dummies were included to incorporate seasonality.

Empirical Results

A unit root test on the five prices was conducted to determine the order of integration of each individual series. Table 2 summarizes the Augmented Dickey-Fuller (ADF) test on the level and first differences of each series. The tests show that the levels of all selected oil prices, except for palm oil, are non-stationary at the 5 percent significance level. However, ADF tests reject the null of a unit root for the first differences of any of the oil prices. Hence, four of the selected five oil prices are integrated of order one.

Based on the unit root test result, we investigated whether there exists one or more cointegration vectors among the five price series. Prior to adopting Johansen's (1988) maximum likelihood procedure, the optimal order of lag, which is the value of *n* in equation (1), needs to be determined. Based on the Schwarz Loss, and Hannan and Quinn measures on alternative lags from unrestricted VARs fit to the five prices in levels, an optimal length of one lag was selected.

Given a lag order of one, a series of trace tests for cointegration were conducted and summarized in Table 3. The table is set up following the sequential testing procedure suggested by Johansen (1992), where we begin testing for zero cointegrating vectors (r=0) with the constant in the cointegrating space. If we reject the first test, we move on to test r=0 with the constant outside the cointegrating space. If we reject this hypothesis, we return to tests of r less than or equal to 1, with the constant inside the cointegrating space. We continue until we first fail to reject the null hypothesis. In this study, the trace tests suggest that one cointegrating vector with the constant inside the cointegrating space exists among these five series.

Given only one cointegration vector present in the five oil prices, it is possible that one or more of the markets will not be a part of this specific cointegration vector. Table 4 presents tests in which each market is excluded from the cointegration space. The null hypothesis for each row of the table is that the market listed in the far left-hand column is not in the cointegration space. The test is a distributed chi-square test with one degree of freedom. We fail to reject the null hypothesis for sunflower and crude oil prices, suggesting these two oil prices are not part of this specific cointegrating vector.

Weak-exogeneity tests were conducted to determine which markets may not respond to perturbations in any of the long run equilibrium (cointegrating vectors) (Table 5). Using a 5% significance level, we determine that most oil prices, except crude oil price, appear to restore their long-run equilibriums when new information is introduced. This test result is expected since crude oil price presumably has the least dependence on other oil prices. Hence, the crude oil price is likely to be exogenous.

Applying directed acyclic graphs mechanism to the variance-covariance matrix of residuals from the ECM in equation (2), we obtain the contemporaneous causal relationships among the five oil prices. The structure is illustrated in Figure 2(a). It shows that, in contemporaneous time (one week in this study), each edible oil price will react to shocks in other edible oil markets. The four edible oil markets are well linked, although the causality cannot be determined. The crude oil price is exogenous in the contemporaneous period. In order to determine the causal direction among the four edible oil prices, we select a sub-period from the data set, the pre-U.S. vs. Iraq war period (1999:1:7 – 2003:3:13), and apply the same maximum likelihood procedure to obtain the variance-covariance matrix from the ECM model. The directed acyclic graph derived from the new variance-covariance matrix is presented in Figure 2(b). In this graph, in addition to crude oil price, palm oil price is also exogenous. Furthermore, in contemporaneous time, new information emanates from palm oil price and flows to soybean and sunflower oil prices, reaching a sink in rapeseed oil price. This may be a surprise since palm oil is not as popular as other vegetable oils (e.g. soybean oil) for food use because of its high saturated fat content. However, palm oil is currently the most economic edible oil; a great number of developing countries consume it (e.g. China, India, and Indonesia) and it is widely used for industrial purposes (USDA). World production of palm oil is primarily concentrated in

Malaysia and Indonesia, therefore, any factor perturbing the palm oil supply in these countries (e.g. policy or weather) may affect the world palm oil market. As a result, the palm oil market can become the source of shocks in contemporaneous time.

It is recognized that the estimated coefficients of equation (2) do not have direct interpretation. In which case, innovation accounting may be the best description of the dynamic structure (Sims; Lutkepohl and Reimers; Swanson and Granger). Therefore, we generated two moving average presentations, the forecast error variance decomposition and the impulse response functions, from the estimated coefficients. Table 6 summarizes the forecast error variance decomposition, which relates the percentage of the forecast error uncertainty accounted for by new information from each market in each of the five oil prices. These numbers partition the uncertainty in each class at horizons of zero, one, four and twenty-six weeks ahead. For soybean oil, the uncertainty associated with current prices is explained by current period shocks in its own price [72.96%] and shocks in palm oil price [27.04%]. If we move one period (one week) ahead, the uncertainty in world soybean oil price is still primarily influenced by itself [74.38%] and the palm oil price [25.60%], though the influence of itself has increased while palm oil has less of an impact. At four weeks (or one month) ahead, the influence of itself on its variation is increasing even more. Meanwhile, the influence of crude oil price has emerged, although it is very modest. At the longer horizon of twenty-six weeks (about half of a year), the variation of world soybean oil price is dominated by its own shocks [86.98%], while crude oil price's influence is still modest [0.34%]. For other edible oil prices, a similar pattern is observed: the variation in edible oil prices in the short run is primary affected by their own shocks; however, at a longer horizon, the influence of shocks in soybean oil price becomes a significant factor influencing the uncertainty of the edible oil prices (31.82% – 75.01%).

This is expected since soybean oil is the most widely produced and distributed vegetable oil. The evidence presented in Table 6 indicates soybean oil price leads edible oil prices in the long run, which corresponds to previous studies (FAPRI; Labys)

The influence of shocks in crude oil prices on the variation in edible oil prices is small. Among the edible oils, variation in palm oil price is affected most by crude oil price although the magnitude is modest (<3%), followed by the rapeseed oil. As expected, crude oil price is largely exogenous among the five markets either in contemporaneous time or over a longer horizon.

Figure 3 shows the dynamic response of each series to a one-time shock in each series. The responses are normalized by dividing each response by the historical standard deviation of the innovation in each series. This allows us to compare responses across prices. The pattern in Figure 3 illustrates the strong influence of soybean oil price (soy_oil) on every other edible oil price. The information illustrated in Figure 3 corresponds with that discussed above from Table 6: soybean oil price dominates the edible oil markets in the long-run.

Concluding Remarks

Because of the expanding edible oil markets and the emerging demand for biodiesel resulting from surging crude oil price and environmental concerns, analysis is carried out to examine the interdependence between edible oil prices and to develop a better understanding of the dynamics between vegetable and crude oil prices. This study selects four internationally traded edible oils (soybean, rapeseed, sunflower and palm oil) along with a world crude oil price for analysis. The data consists of 378 weekly observations extending from the first week of January, 1999 to the fourth week of March, 2006.

Employing time-series mechanisms, we found one cointegration vector among the five evaluated oil prices, reflecting the extent of substitution among the edible oils. Directed acyclic graphs analysis indicates that palm oil price initiates the information flow while rapeseed market is the information receiver in contemporaneous time. In the long run, soybean oil is the most influential player among edible oil markets: variation in soybean oil prices explains about 32-75% of other edible oil prices. We do not find that shocks in crude oil prices have a significant influence on the variation of edible oil prices. Possibly the influence of crude oil price on edible oils will grow if high oil prices continue and edible oils become an increasing source of biodiesel. This area deserves further research because of the expected importance of biodiesel in the future.

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Table 1. Descriptive Statistic Summary of Weekly World Edible Oil and Crude Oil Prices

Prices	Unit	Mean	S.D.	Min.	Max.	C.V.
Soybean oil	US$/ton	472.03	107.53	287.00	710.00	0.23
Sunflower oil	US$/ton	562.82	106.74	335.00	745.00	0.19
Rapeseed oil	US$/ton	523.16	135.94	318.00	754.00	0.26
Palm oil	US$/ton	394.68	80.80	227.00	645.00	0.20
Crude oil	US$/barrel	29.85	11.64	9.31	60.75	0.39

Table 2. Unit-root Test on Weekly World Edible Oil and Crude Oil Prices

Prices	Level	First Difference
Soybean oil	-1.36 (0) #	-19.90 (0)
Sunflower oil	-1.42 (1) #	-16.76 (0)
Rapeseed oil	-0.29 (0) #	-19.13 (0)
Palm oil	-3.11 (0)	-16.86 (0)
Crude oil	-0.63 (0) #	-15.50 (0)

Note: number in parenthesis represents the optimal length of lag on the dependent variable in the Augmented Dickey-Fuller test. “#” indicates the null hypothesis of unit roots for the series is failed to be reject at the 5 percent significance level. Critical value at 5% level is -2.869 (Fuller).pothesis of unit roots for the series is failed to be reject at the 5 percent significance level. Critical value at 5% level is -2.869 (Fuller).

Table 3. Trace Test on Weekly World Edible Oil and Crude Oil Prices

R	T*	C(5%)*	*D**	T	C(5%)	*D*
= 0	90.87	75.74	Reject	88.44	68.68	Reject
≤ 1	39.82	53.42	F.T.R #	38.52	47.21	F.T.R
≤ 2	17.31	34.80	F.T.R	16.12	29.38	F.T.R
≤ 3	7.44	19.99	F.T.R	6.28	15.34	F.T.R
≤ 4	2.71	9.13	F.T.R	1.54	3.84	F.T.R

Note: * represents the constant is in the cointegration vector. F.T.R = “Fail to Reject”.

Table 4. Test on Exclusion of Selected Edible Oil and Crude Oil Prices from Cointegration Space

Prices	Chi-Squared Test	Decision
Soybean oil	23.96	Reject
Sunflower oil	1.47	F.T.R
Rapeseed oil	7.38	Reject
Palm oil	19.45	Reject
Crude oil	3.61	F.T.R

Note: critical value of χ_1 is 3.84. F.T.R = "Fail to Reject".

Table 5. Test on Weak-exogeneity of Selected Edible Oil and Crude Oil Prices from Cointegration Space

Prices	Chi-Squared Test	Decision
Soybean oil	5.66	Reject
Sunflower oil	5.46	Reject
Rapeseed oil	18.04	Reject
Palm oil	22.53	Reject
Crude oil	2.59	F.T.R.

Note: critical value of χ_1 is 3.84. F.T.R = "Fail to Reject".

Table 6. Forecast Error Variance Decomposition of Selected Edible Oil and Crude Oil Prices from Cointegration Space

Horizon	Soybean oil	Sunflower oil	Rapeseed oil	Palm oil	Crude oil
			Soybean oil		
0	72.96	0.00	0.00	27.04	0.00
1	74.38	0.00	0.02	25.60	0.00
4	77.82	0.00	0.16	21.97	0.04
26	86.98	0.01	1.39	11.28	0.34
			Sunflower oil		
0	12.04	69.47	0.00	18.49	0.00
1	13.29	69.05	0.02	17.64	0.00
4	16.86	67.52	0.18	15.40	0.04
26	31.82	58.13	1.72	7.92	0.41
			Rapeseed oil		
0	26.95	2.65	57.53	12.87	0.00
1	30.61	2.69	54.83	11.86	0.01
4	40.94	2.75	46.97	10.02	0.13
26	75.01	2.43	19.15	2.22	1.19
			Palm oil		
0	0.00	0.00	0.00	100.00	0.00
1	0.38	0.00	0.11	99.49	0.02
4	4.02	0.01	1.13	94.59	0.25
26	40.36	0.14	10.36	46.77	2.37
			Crude oil		
0	0.00	0.00	0.00	0.00	100.00
1	0.02	0.00	0.01	0.01	99.96
4	0.15	0.01	0.14	0.06	99.64
26	0.94	0.34	1.98	0.71	96.04

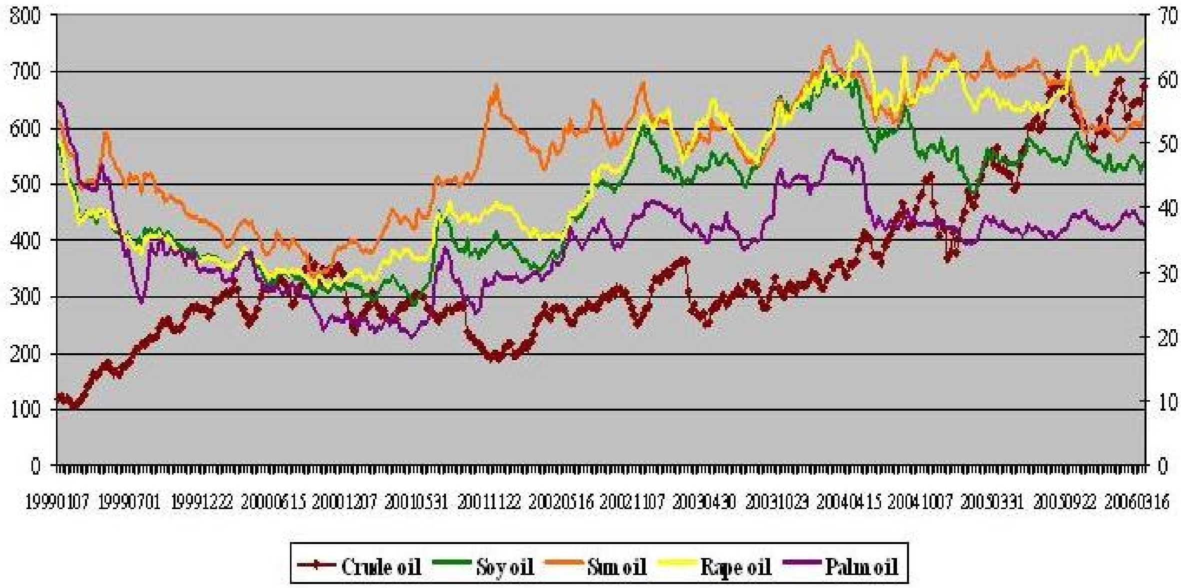

Figure 1. Plot of Selected Edible Oil and Crude Oil Prices

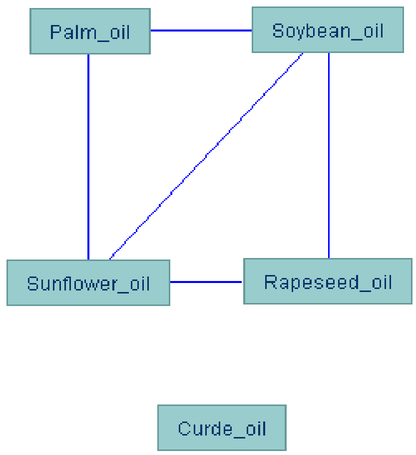

Figure 2(a). Directed Acyclic Graph on Innovation from the Error Correction Model Fit to Edible Oil and Crude Oil Prices, 1999:1:7 – 2006:3:30

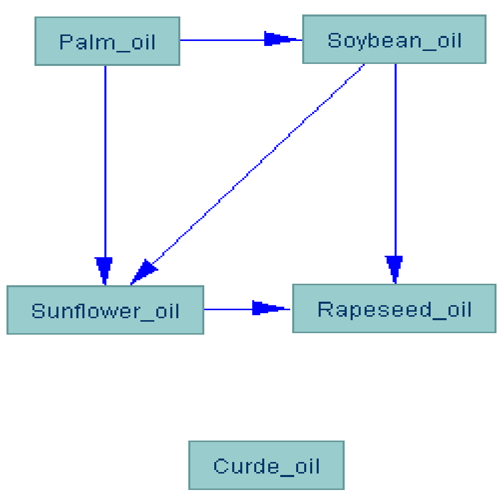

Figure 2(b). Directed Acyclic Graph on Innovation from the Error Correction Model Fit to Edible Oil and Crude Oil Prices, 1999:1:7 – 2003:3:13

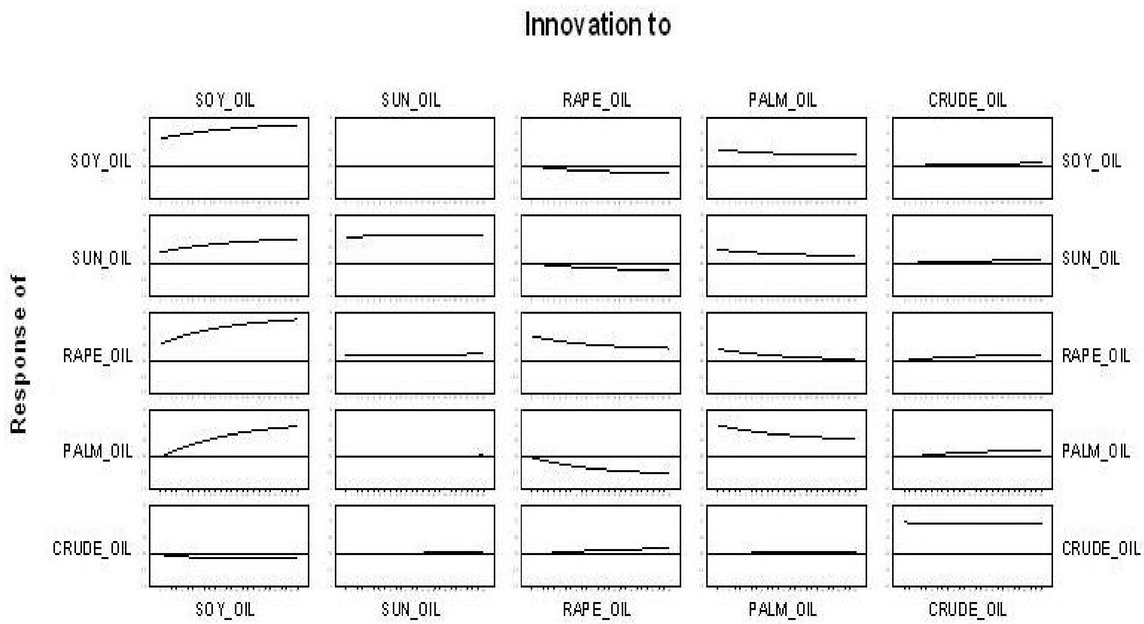

Figure 3. Impulse Response Function of Each Prices to a One-Time-Only Shock (Innovation) in Each Series