Price Discovery of World and China Vegetable Oil Markets and Causality with Non-Gaussian Innovations

Senarath Dharmasena
Department of Agricultural Economics
Texas A&M University
sdharmasena@tamu.edu

Lu Fang
Department of Agricultural Economics
Texas A&M University
flapply@tamu.edu

David A. Bessler
Department of Agricultural Economics
Texas A&M University
d-bessler@tamu.edu

Jing Wang
Northeast Agricultural University – China
wangjingneau@gmail.com

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1. Introduction

Vegetable oil is one of the most important edible oils in China (Oil China, 2012). In 2010, the total consumption of vegetable oil in China was 27 million tons. This is 93% increase compared to year 2000, with average annual growth of about 6.8% from 2000 to 2010 (Xu and Xie, 2012). Soybean and rapeseed oil have been the most widely used vegetable oils in China for decades. Consumption of soybean oil was about 10 million tons in 2010 accounting for 41% total domestic vegetable oil consumption (Xu and Xie, 2012). While soybean oil consumption is ranked number one, rapeseed oil consumption comes third. Rapeseed oil plays a vital role in traditional Chinese cooking. Furthermore, data from the China Statistics Bureau showed that China is the largest rapeseed oil consumer in the World. According to the National Food Security Long-term Plan (2008-2020) of China, in 2020 the per capita annual consumption of vegetable oil will reach 20kg, and the total consumption will reach 29 million tons. These statistics show the magnitude of the current vegetable oil market in China. Due to the lack of domestic production of vegetable oils to meet the demand, China has been importing vegetable oil form the World market. According to the statistics of Customs Information Network, from January to July 2012, China imported a total of 400 million tons of edible vegetable oils. This is an increase of 18% compared to 2011, and is worth $ 4.7 billion.

According to Cheng (2012), 92% of soybean oil and 20% of rapeseed oil consumed in China are imported. This increasing dependence on international market for vegetable oil potentially has an impact on Chinese domestic price of such oils.

In and Inder (1997) used co-integration methods to study long-run relationships between eight types of vegetable oils in the World market. Yu *et al*. (2006) investigated the relationship among soybean, sunflower, rapeseed and palm oils along with one weighted average World crude oil price and described the long-run dynamic relationship between vegetable and crude oil prices. Wang (2008) examined the linkage of soybean oil futures price between China and United States. The results showed a long-run equilibrium relationship between futures prices and China spot price. Liu *et al*. (2012) estimated the relationship between the price of the soybean oil and soybeans in China. They found that the soybean oil price has a positive relationship with the price of soybeans in China.

The extant literature on dynamics of vegetable oil prices shows that most studies centered attention to World vegetable oil prices, but failed to relate it to the dynamics of China domestic vegetable oil price. The only exception to this is Wang *et al.*, (2013), where dynamic movements of world and China vegetable oil prices were modeled in an error correction framework. However, Wang *et al.,* (2013) not only assumed a Gaussian distribution in their modeling framework, but also did not investigate rich set of information hidden in innovations of the error correction model. Our study sheds light on modeling price discovery of world and China vegetable oil markets more realistically assuming non-Gaussian innovations. Moreover, using rich set of information hidden in innovations of vector error correction model, we establish price discovery causal patterns using artificial intelligence and directed acyclic graphs (DAGs), again assuming non-Gaussian innovations (Shimizu *et al.*, 2006).

2. Objectives

The specific objectives of this study are (1) to estimate a vector error correction model (VECM) (or seasonal VECM (Beaulieu and Miron, 1993; Johansen and Schaumburg, 1999) if seasonal unit roots are present in data) for world and China vegetable oil markets; (2) to perform innovation accounting using impulse response functions and error variance decompositions; (3) to develop causality patterns of world and China vegetable oil prices obtained through directed acyclic graphs applied to the innovations from VECM assuming non-Gaussian innovations; (4) to identify structural breakpoints (if any) that affect the dynamic patterns of world and China vegetable oil prices; and (5) to perform policy analysis based on graphical causal structures obtained from objective.

3. Methodology

3.1 Vector error correction model (VECM), cointegration analysis, innovation accounting and factorization of residuals

A vector error correction model (VECM) is applied as a basis for the empirical analysis. Existing literature has well discussed the cointegration analysis and vector error correction model (Johansen, 1991; Johansen and Juselius, 1990, 1994). A VECM with *k*-1 lags is presented as

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \mu + e_t \; (t = 1, \dots, T) \quad (1)$$

where $\mathrm{X_t}$ is a (4×1) vector including 4 nonstationary vegetable oil prices (price of Chinese rapeseed oil, price of Chinese soybean oil, price of world rapeseed oil, price of world soybean oil), $\Delta\mathrm{X_t}$ is the difference between $\mathrm{X_t}$ and $\mathrm{X_{t-1}}$, Π and Γ_i are (4×4) coefficient matrices, μ is a (4×1) vector of constants, and $\mathrm{e_t}$ is an iid (4×1) vector of Gaussian innovations with zero mean and variance covariance matrix Σ.

The coefficient matrix Π could be factorized as $\Pi = \alpha\beta^{'}$, where β $(4 \times r)$ is the cointegrating space capturing the long-run dynamics and α $(4 \times r)$ is the short-run response to the long-run relations. As the rank of Π, r is the number of cointegrating vectors ($r \leqq 4$). Testing hypotheses on cointegrating space β could facilitate the identification of long-run structure, and testing hypotheses on α and Γ_i could facilitate the identification of the short-run structure (Johansen and Juselius, 1994; Johansen, 1995). The contemporaneous structure can be identified through directed acyclic graph analysis based on the observed innovations (Pearl, 1995, 2000; Spirtes and Scheines, 2000).

Following the studies of Phillips (1996), Wang and Bessler (2005) and Park, Mjelde and Bessler (2008), the number of cointegrating vectors is tested simultaneously with the test of lag length using Schwarz-loss and Hannan and Quinn-loss information criteria. Whether to include a constant within the cointegrating space is incorporated into this procedure as well.

Given the number of cointegrating vectors, the hypothesis test of exclusion is conducted on the cointegrating space β to determine whether a particular series enters into the long-run equilibrium. The test is as follows

$\mathcal{H}_1$: $\beta = H\varphi$

The null hypothesis is that a particular series does not entering into the long-run equilibrium or the *i*th column of $\beta^{'}$ is all zero.

The hypothesis test of weak exogeneity is carried out on α to determine whether a particular series responds to the deviation from the long-run equilibrium. The test is as follows

$\mathcal{H}_2$: $\alpha = H\psi$

The null hypothesis is that a particular series does not respond to the perturbation in the long-run relation or the *i*th row of α is all zero.

Further analysis of short-run structure involves the examination of Γ_i. However, as the level VAR, the coefficients of the VECM are difficult to interpret. As suggested by Sims (1980), Lutkepohl and Reimers (1992), and Swanson and Granger (1997), the innovation accounting procedures like impulse response functions and forecast error variance decomposition may be the best way to summarize the short-run dynamic structure. In this paper, the VECM in Eq. (1) with *k*-1 lags is converted to its corresponding level VAR with *k* lags:

$$X_t = (1 + \Gamma_1 + \Pi)X_{t-1} - \sum_{i=1}^{k-2}(\Gamma_i - \Gamma_{i+1})X_{t-i-1} - \Gamma_{k-1}X_{t-k} + \mu + e_t \ (t = 1, \dots, T) \qquad (2)$$

Based on the equivalent VAR representation, innovation accounting is conducted using moving average representation.

One critical problem of innovation accounting is how to explore the contemporaneous correlations of variables. Early work used Choleski factorization to set up a lower triangular contemporaneous causal ordering among variables. The application of Choleski factorization may cause problems like unrealistic assumption of lower triangular causal ordering and seriously misleading innovation accounting results (Bernanke, 1986; Sims, 1986; Swanson and Granger, 1997; Yang and Bessler, 2004). Structural factorization suggested by Bernanke (1986) is a more recent approach to identify the contemporaneous structure. The observed innovations e_t is transformed into orthogonal innovations v_t, which are the driving sources of variation in the data:

$$\mathrm{A}e_t = v_t \qquad (3)$$

Instead of imposing lower triangular structure as Choleski factorization, structural factorization allows more general causal orderings in matrix A. In this paper, A matrix is a (4×4) matrix with diagonal of ones:

$$A = \begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} \\ a_{21} & 1 & a_{23} & a_{24} \\ a_{31} & a_{32} & 1 & a_{34} \\ a_{41} & a_{42} & a_{43} & 1 \end{bmatrix} \qquad (4)$$

As discussed later, directed acyclic graph (DAG) technique will be used to assign zero restrictions in matrix A. By pre-multiplying Eq. (2) by A, Eq. (5) is obtained for the estimation of usual innovation accounting procedures:

$$AX_t = A(1 + \Gamma_1 + \Pi)X_{t-1} - A\sum_{i=1}^{k-2}(\Gamma_i - \Gamma_{i+1})X_{t-i-1} - \mathrm{A}\Gamma_{k-1}X_{t-k} + A\mu + Ae_t \ (t = 1, \dots, T) \quad (5)$$

Although the structural factorization allows more general causal flows, most of the previous literature still relies on subjective or theory-based information to explore contemporaneous structure (Bessler and Yang, 2003). Swanson and Granger (1997) suggested a data-determined approach to sort out contemporaneous causal orderings. In this paper, the recently developed directed acyclic graph (DAG) technique will be applied to identify the contemporaneous structure and the innovation accounting procedures will be conducted based on the DAG-based structural factorization.

3.2 Directed graphs theory

A directed graph is a graph summarizing the causal flows among a set of variables (or vertices) (Pearl, 2000). A more vivid description of the directed graph is a pipeline transferring water standing for dependence and independence information flow (Spirtes, Glymour and Scheines, 2000). The directed graph consists of vertices (variables), marks (symbols attached to the end of undirected edges), and ordered pairs (edges). Arrows exhibit the direction of information flow in directed graphs. If there are no edges connecting variable X and variable Y, the two variables are conditionally uncorrelated. An undirected edge like $X - Y$, indicates variable X and variable Y are conditionally correlated. However, whether X causes Y or vice versa could not be determined. If there is a directed edge connecting variable X and variable Y like $X \rightarrow Y$, not only correlation but also causation could be inferred (variable X causes variable Y). $X \leftrightarrow Y$ describes a bi-directed edge, indicating that there is an omitted variable which causes both X and Y. In this paper, only directed acyclic graphs (DAGs) are considered to describe the contemporaneous causal relations among variables. Therefore, the resulting directed graphs will contain no directed cyclic paths or have no path that leads away from a variable only to return to that same variable.

Several algorithms have been developed to generate the DAGs. One of the earliest and most popular algorithms is PC algorithm (Spirtes, Glymour and Scheines, 2000). PC algorithm starts with a complete undirected graph and searches causal flows based on conditional independence. First, the edges of the graph are removed sequentially if the correlation or partial correlation (conditional correlation) of pairs of variables is zero. Then the notion of sepset (the conditioning variable(s) on removed edges between two variables is called the sepset of the variables whose edge has been removed) is used to determine the causal direction of the remaining edges.

PC algorithm is implemented based on the assumption of Gaussian distributed variables. Under this assumption, second-order moments of the variables could provide required information of probability distribution and partial correlation. Therefore, these is no need for higher-order moment structures (Shimizu, Hoyer et al., 2006; Shimizu, Hyvarinen et al., 2012). However, since more than one graph could lead to the same probability distribution (e.g. $x \leftarrow y \rightarrow z$ and $x \rightarrow y \rightarrow z$), PC algorithm could not distinguish between the observationally equivalent graph structures (same joint probability density) (Pearl, 2000). In the graph, the indistinguishable or equivalent structures are characterized by undirected edges (Drewek 2010).

Different from PC algorithm, the recently developed Linear Non-Gaussian Acyclic Models (LiNGAM) algorithm developed by Shimizu, Hoyer et al. (2006) presumes independent non-Gaussianity (more than covariance information) of the variables. Based on this assumption, higher-order statistics could be used to distinguish the causal graphs that PC algorithm fails to. LiNGAM algorithm is conducted by first applying independent component analysis (ICA) to estimate a mixing matrix. Assume a vector of observed variables $\mathrm{X} = \{x_{1,}x_{2,\ldots,}x_m\}$ and each variable x_i $(i = 1, \ldots, m)$ is a linear function of the earlier variables and the disturbance e_i

$$x_i = \sum_{k(j)<k(i)} b_{ij} x_j + e_i \tag{6}$$

where $k(i)$ is a causal order of x_i, x_j directly causes x_j, and e_i is the independent and non-Gaussian disturbance. By subtracting out the mean of each x_i, generated system of equations is:

$$X = BX + e \tag{7}$$

where *B* stands for the coefficient matrix. Solving for *X* will give Eq. (8):

$$X = Ae \tag{8}$$

where $A = (I - B)^{-1}$. The mixing matrix A is estimated by ICA. This procedure emphasizes the non-Gaussianity of disturbances, since many different mixing matrices yield the exact same covariance matrix (implying the exact same Gaussian joint density) if the disturbances are Gaussian (Hyvärinen, Karhunen and Oja, 2004). After obtaining the mixing matrix A, a series of transformation, permutation and normalization are followed to generate a strictly lower triangular matrix $\tilde{B}$ (an estimate of B) for causal ordering. Then higher-order moment structures are used to construct tests of model fit and determine the causal directions among variables (Shimizu, Hoyer et al., 2006; Shimizu, Hyvärinen et al., 2006; Shimizu, Hyvarinen et al., 2012).

In this paper, the structural residuals of all four series are non-Gaussian (as discussed later). Therefore, LiNGAM algorithm will be applied to identify more exact contemporaneous causal pattern. As indicated by Shimizu and Kano (2008), the more non-Gaussian the data are, the more accurate the causal structure identified by LiNGAM is.

4. Data

Four vegetable oil price series are considered, which are price of Chinese rapeseed oil (C_rapeseed), price of Chinese soybean oil (C_soybean), price of world rapeseed oil (W_rapeseed) and price of world soybean oil (W_soybean). Monthly data for the two Chinese series are collected from China Price Yearbook while monthly data for the two world series are from World Bank database. The data cover the period from January 1994 to December 2010, yielding 204 observations. All the four price series are measured as US dollars per metric ton and are transformed into logarithmic form. Figure 1 shows the plots of logarithmic prices. The descriptive statistics of the four price series are provided in Table 1.

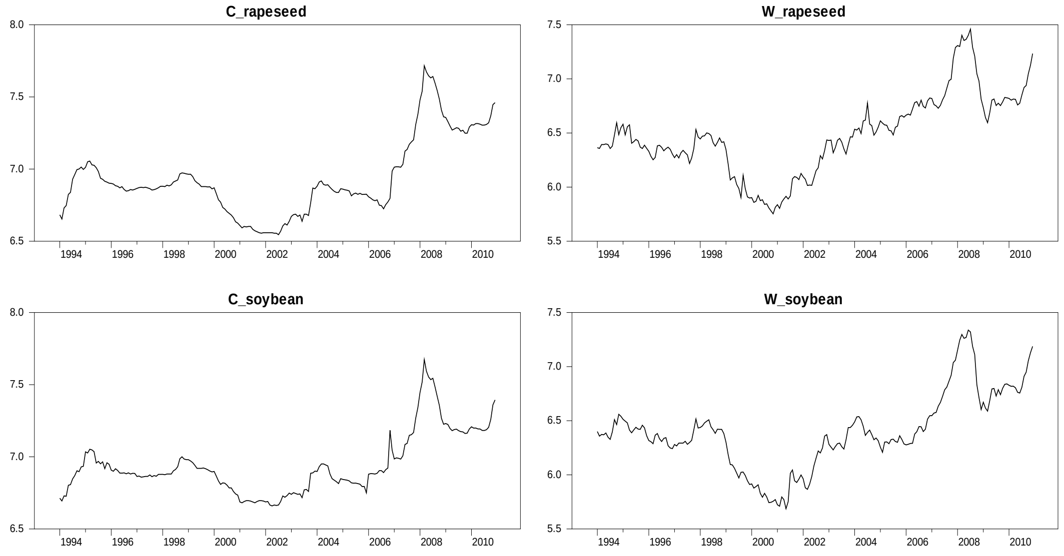

Fig.1. Monthly logarithmic prices (January 1994 to December 2010)

Table 1 List of descriptive statistics

	Mean	Median	Maximum	Minimum	SD
C_rapeseed	6.93	6.88	7.72	6.55	0.26
C_soybean	6.94	6.89	7.67	6.66	0.21
W_rapeseed	6.48	6.45	7.46	5.75	0.37
W_soybean	6.40	6.37	7.34	5.69	0.35

5. Empirical Results

5.1 Stationarity

One important questions involved in the estimation of time series data is the stationarity of each series. If the series are nonstationary, the usual ordinary least squares estimation of the autoregressive model may lead to spurious regression results (Granger and Newbold, 1974). The well-used unit root tests, the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and the Phillips–Perron test (Phillips and Perron, 1988), are considered. The Elliott-Rothenberg-Stock test (Elliott, Rothenberg and Stock, 1996) is also used to increase the power of the unit root test. According to the results from Table 2, all the four series are nonstationary in level with the presence of unit roots, but stationary after first differencing.

However, Engle and Granger (1987) argued that stationary data achieved by first differencing may fail to capture the long-run information. As a result, when all the seriese are integrated of order one, further test of cointegration is needed to detect the potential cointegrating relations among the variables.

Table 2 Tests for unit root

Variables	ADF	Phillips-Perron	Elliott-Rothenberg-Stock
Level			
C_rapeseed	-1.0159	-1.2756	-0.6967
C_soybean	-0.8989	-1.644	-0.5692
W_rapeseed	-0.6649	-1.7759	-0.8854
W_soybean	-0.6576	-1.5894	-1.3298
1st differences			
C_rapeseed	-5.1371***	-9.8969***	-3.1429***
C_soybean	-6.2624***	-13.0969***	-3.8107***
W_rapeseed	-8.5005***	-12.5336***	-5.1128***
W_soybean	-4.9614***	-9.9131***	-3.3454***

Notes: *, ** and *** denotes rejection of the null hypothesis of presence of unit roots for ADF tests, Phillips-Perron tests and Elliott-Rothenberg-Stock tests at 10%, 5% and 1% significance levels

5.2 Choice of lag length and cointegrating rank

The order of lags and number of cointegrating vectors are tested simultaneously using both Schwarz-loss and Hannan and Quinn-loss metrics. Two cases, with a constant inside of the cointegrating space β and without a constant inside of the cointegrating space β are considered (Table 3a and Table 3b). Accordingly, both loss metrics indicate that the optimal lag length is 2, the number of cointegrating vectors is 1 and the cointegrating space β should contain a constant (minimization of the loss metrics). The subsequent examinations will be based on a VECM with these model specifications.

Table 3a Test of lag length and number of cointegrating vectors (Schwarz-loss metric)

	With a constant			Without a constant		
	r<=1	r<=2	r<=3	r<=1	r<=2	r<=3
lag=1	-25.442	-25.421	-25.386	-25.368	-25.372	-25.361
lag=2	**-25.513**	-25.451	-25.391	-25.440	-25.402	-25.367
lag=3	-25.259	-25.197	-25.128	-25.184	-25.146	-25.102

Note: lags 1-3 and conintegrating rank 1-3 are applied sequentially to the vector error correction model (VECM). Schwarz loss = $log|\Sigma| + (m \times k)(logT)/T$, where Σ is the variance and covariance matrix of residuals, $|\ \ |$ is the determinant operator, *m* indicates the number of endogenous variables in each equation, *k* indicates the number of regressors in each equation, and *T* is the total number of observations in each series.

Table 3b Test of lag length and number of cointegrating vectors (Hannan and Quinn-loss metric)

	With a constant			Without a constant		
	r<=1	r<=2	r<=3	r<=1	r<=2	r<=3
lag=1	-25.520	-25.557	-25.561	-25.475	-25.528	-25.546
lag=2	**-25.747**	-25.744	-25.723	-25.703	-25.714	-25.708
lag=3	-25.651	-25.647	-25.617	-25.604	-25.615	-25.601

Note: lags 1-3 and conintegrating rank 1-3 are applied sequentially to the vector error correction model (VECM). Hannan and Quinn loss = $log|\Sigma| + (2.01)(m \times k)(\log(logT))/T$, where Σ is the variance and covariance matrix of residuals, $|\ \ |$ is the determinant operator, *m* indicates the number of endogenous variables in each equation, *k* indicates the number of regressors in each equation, and *T* is the total number of observations in each series.

5.3 Tests on long-run structure

A series of tests are conducted to identify the long-run structure among these prices. The first question is whether the single cointegrating relation is caused since one of the price series is stationary by itself or since there is a linear combination of two or more price series. Table 4 shows the results of stationarity test and none of the four series is stationary by itself.

Table 4 Test of stationarity (given one cointegrating vector)

Series	Chi-squared	P-value	Decision
C_rapeseed	30.813	0.000	R
C_soybean	30.067	0.000	R
W_rapeseed	28.146	0.000	R
W_soybean	28.01	0.000	R

Critical value at 5% significance level given one cointegrating vector is 7.815. The null hypothesis is that the particular series is stationary. The heading "Decision" relates to the decision to reject (R) or fail to reject (F) the null hypothesis at 5% significance level. Under the null hypothesis, the test statistics is distributed as χ^2 with three degrees of freedom.

Given one cointegrating vector, it is possible that certain series may not enter into the long-run relation. The test of exclusion is conducted on the cointegrating space β to determine whether a particular series is excluded from the long-run equilibrium. Based on the results from Table 5, the null hypothesis of exclusion from long-run relation fails to be rejected for C_soybean and is rejected for C_rapeseed, W_rapeseed and W_soybean. Therefore, the second series C_soybean is excluded from the conintegrating relation, yielding the restriction expressed as Eq. (9) with second column of β being zero (a non-zero constant is included in the cointegrating space):

$$\begin{bmatrix} \beta_{11} \\ \beta_{21} \\ \beta_{31} \\ \beta_{41} \\ \beta_{51} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varphi_{11} \\ \varphi_{21} \\ \varphi_{31} \\ \varphi_{41} \end{bmatrix} \tag{9}$$

Table 5 Test of exclusion (given one cointegrating vector)

Series	Chi-squared	P-value	Decision
C_rapeseed	6.737	0.009	R
C_soybean	1.609	0.205	F
W_rapeseed	8.169	0.004	R
W_soybean	14.301	0.00	R

Critical value at 5% significance level given one cointegrating vector is 3.841. The null hypothesis is that the particular series is excluded from the single long-run relation. The heading "Decision" relates to the decision to reject (R) or fail to reject (F) the null hypothesis at 5% significance level. Under the null hypothesis, the test statistics is distributed as χ^2 with one degree of freedom.

In order to test whether each series responds to the perturbation in the single long-run relation, the test of weak exogeneity is conducted on α. The test results are exhibited in Table 6. The null hypothesis is that a particular series is weakly exogenous and does not adjust to the perturbation in the long-run relations. Therefore, price series C_soybean, W_rapeseed and W_soybean do not adjust to the deviation from the long-run equilibrium. The second, third and fourth rows of α are restricted to be zero as in Eq. (10):

$$\begin{bmatrix} \alpha_{11} \\ \alpha_{21} \\ \alpha_{31} \\ \alpha_{41} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \psi \tag{10}$$

Table 6 Test of weak exogeneity (given one cointegrating vector)

Series	Chi-squared	P-value	Decision
C_rapeseed	13.209	0.000	R
C_soybean	1.382	0.240	F
W_rapeseed	3.321	0.068	F
W_soybean	1.712	0.191	F

Critical value at 5% significance level given one cointegrating vector is 3.841. The null hypothesis is that the particular series does not respond to the perturbation in the long-run relation. The heading "Decision" relates to the decision to reject (R) or fail to reject (F) the null hypothesis at 5% significance level. Under the null hypothesis, the test statistics is distributed as χ^2 with one degree of freedom.

Based on the combined restrictions on β and α in Eq. (9) and Eq. (10), the restricted model is tested. The resulting test statistics is $\chi^2(4) = 19.15$ with a p-value of 0.001. The rejection of null hypothesis indicates that the combined restrictions expressed as Eq. (9) and Eq. (10) are reasonable. As a result, the coefficient matrix Π is as follows (the component associated to C_rapeseed series in β is normalized into 1):

$$\alpha\beta' = \begin{bmatrix} -0.054 \\ 0 \\ 0 \\ 0 \end{bmatrix} [1.000 \quad 0.000 \quad 0.302 \quad -1.124 \quad -1.724] \tag{11}$$

5.4 Identification of the contemporaneous structure

Based on the innovations from VECM, the DAG is generated using TETRAD V. Since the LiNGAM algorithm relies on the non-Gaussianity of data, the Jarque-Bera test of structural residuals are conducted to detect whether the series are non-Gaussian. As shown in Table 7, only of the structural residuals of four price series is normal, enabling the application of LiNGAM (Spirtes, Glymour and Scheines et al., 2010).

Table 7 Jarque-Bera test of structural residuals

Series	Test statistics	P-value	Decision
C_rapeseed	30.121	0.000	R
C_soybean	62.913	0.000	R
W_rapeseed	3.017	0.221	F
W_soybean	6.486	0.039	R

The null hypothesis is that the structural residual of a particular series is normally distributed. The heading "Decision" relates to the decision to reject (R) or fail to reject (F) the null hypothesis at 5% significance level.

Accordingly, the DAG result is shown in Figure 2. One interesting result is the contemporaneous separation between the Chinese market and the world market with respect to the prices of rapeseed oil and soybean oil. It is possibly due to the construction structure of the world price series. The two world price series are weighted prices by aggregating prices from different countries and regions. The aggregation structure of the data may fail to discover the contemporaneous casual relations between the world market and the Chinese market. This would be a good implication of using disaggregated data for future research. Within each market, the contemporaneous causal relation between rapeseed oil price and soybean oil price is found. However, different types of vegetable oil play different roles in the two markets. In the Chinese market, C_rapeseed leads C_soybean in contemporaneous time. In the world market, information flow is W_soybean causes W_rapeseed. Both C_rapeseed and W_soybean appear to be exogenous.

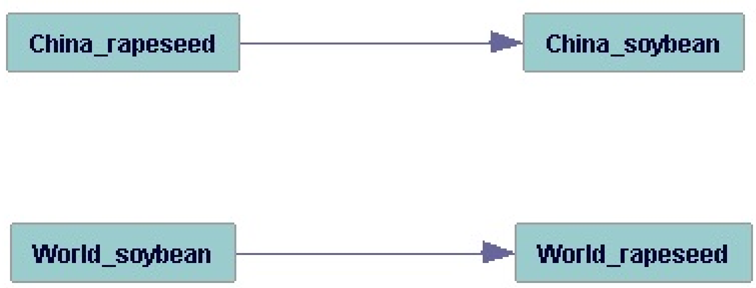

Fig.2. Directed acyclic graph

5.5 Forecast error variance decomposition

To better capture the short-run dynamic structure of the price series, forecast error variance decomposition and impulse response function are conducted. The results of forecast error variance decomposition are presented in Table 8. The decomposition is performed in different horizons, with horizon of zero (contemporaneous time), 1 and 2 months (short horizon), 24 months ahead (longer horizon).

The variation of C_rapeseed is mainly explained by its own innovation at the short horizon (86.7% - 93%). In the long run, however, W_soybean (73.3%) has a substantial influence on C_rapeseed. In addition, C_soybean (1.9%), W_rapeseed (5.1%) and C_rapeseed itself (19.7%) account for the majority of the variation in C_rapeseed. With respect to the variation in C_soybean, it is primarily explained by both innovations of C_rapeseed (25% - 29.8%) and C_soybean itself (54.6% - 74.4%) at all horizons, even though the influence of innovation of C_soybean has some decrease from the short horizon to longer horizon and. Innovation of W_soybean (20%) accounts for part of the variation in C_soybean as well in the long run.

The variation of W_rapeseed is substantially explained by W_rapeseed and W_soybean at all horizons. At contemporaneous time, W_rapeseed accounts for a large proportion of its own variation (86.2%) while W_soybean explains about 13.8% of the variation in W_rapeseed. In the short run, the influence of W_rapeseed (47.7% - 58.7%) and W_soybean (41.2% - 52.0%) are relatively similar. The innovation of W_soybean (72.8%) plays an important role in explaining the variation in W_rapeseed in the long run, and the influence of W_rapeseed diminishes to 26.5%. The W_soybean is highly exogenous at all horizons and its variation is predominantly explained by its own innovation (98.2% - 100%). Innovations of the two Chinese price series have extremely very limited influence on the two world price series.

Table 8 Forecast error variance decomposition

Periods	C_rapeseed	C_soybean	W_rapeseed	W_soybean
	Percentage (%)			
C_rapeseed				
0	100.000	0.000	0.000	0.000
1	93.037	4.569	0.007	2.388
2	86.702	5.325	0.079	7.893
3	80.689	5.591	0.257	13.463
4	75.260	5.587	0.480	18.672
5	70.236	5.461	0.735	23.567
6	65.522	5.270	1.011	28.197
24	19.667	1.968	5.112	73.253
C_soybean				
0	25.603	74.397	0.000	0.000
1	28.769	68.142	0.033	3.056
2	29.541	64.655	0.022	5.782
3	29.784	62.473	0.022	7.721
4	29.764	61.061	0.027	9.148
5	29.623	60.071	0.035	10.272
6	29.418	59.333	0.044	11.205
24	25.098	54.589	0.268	20.045
W_rapeseed				
0	0.000	0.000	86.236	13.764
1	0.082	0.046	58.657	41.216
2	0.279	0.106	47.655	51.961

3	0.431	0.165	42.153	57.251
4	0.522	0.203	38.845	60.430
5	0.573	0.228	36.621	62.578
6	0.599	0.245	35.011	64.145
24	0.434	0.250	26.521	72.795
W_soybean				
0	0.000	0.000	0.000	100.000
1	0.236	0.044	0.429	99.292
2	0.457	0.109	0.607	98.828
3	0.583	0.153	0.697	98.567
4	0.647	0.180	0.756	98.417
5	0.676	0.196	0.801	98.327
6	0.684	0.205	0.838	98.273
24	0.423	0.183	1.160	98.234

5.6 Impulse response function

The results of impulse response functions are shown in Figure 3, presenting the responses of each price series to a one time shock in each series. In each sub-graph, the horizontal axis indicates the horizon (24 months in this paper) and the vertical axis indicates the standardized response.

The impulse response of C_rapeseed to the shock in its own innovation is immediate, positive and strong. However, the strong response doesn't last long but diminishes over time. The response of C_soybean to the shock in C_rapeseed shows positive, large but long lasting impulse. A shock in C_soybean is transferred to an immediate and positive response in C_rapeseed, which dampens to zero thereafter. The response of C_soybean to its own innovation shock is positive, strong and stable over time. The responses of the two world price series to the shocks in C_rapeseed and C_soybean are very small, similar as the results shown in the forecast error variance decomposition.

The shock in W_rapeseed is transferred as relatively small and negative response impulses in C_rapeseed, C_soybean and W_soybean, whereas the shock is transferred to strong and positive and long lasting impulses. These results may imply that W_rapeseed is compensating the imbalances in other price series. A shock in W_soybean has positive influences on all four series. Specifically, a shock in W_soybean is transferred as strong and long lasting response impulses of W_rapeseed and W_soybean.

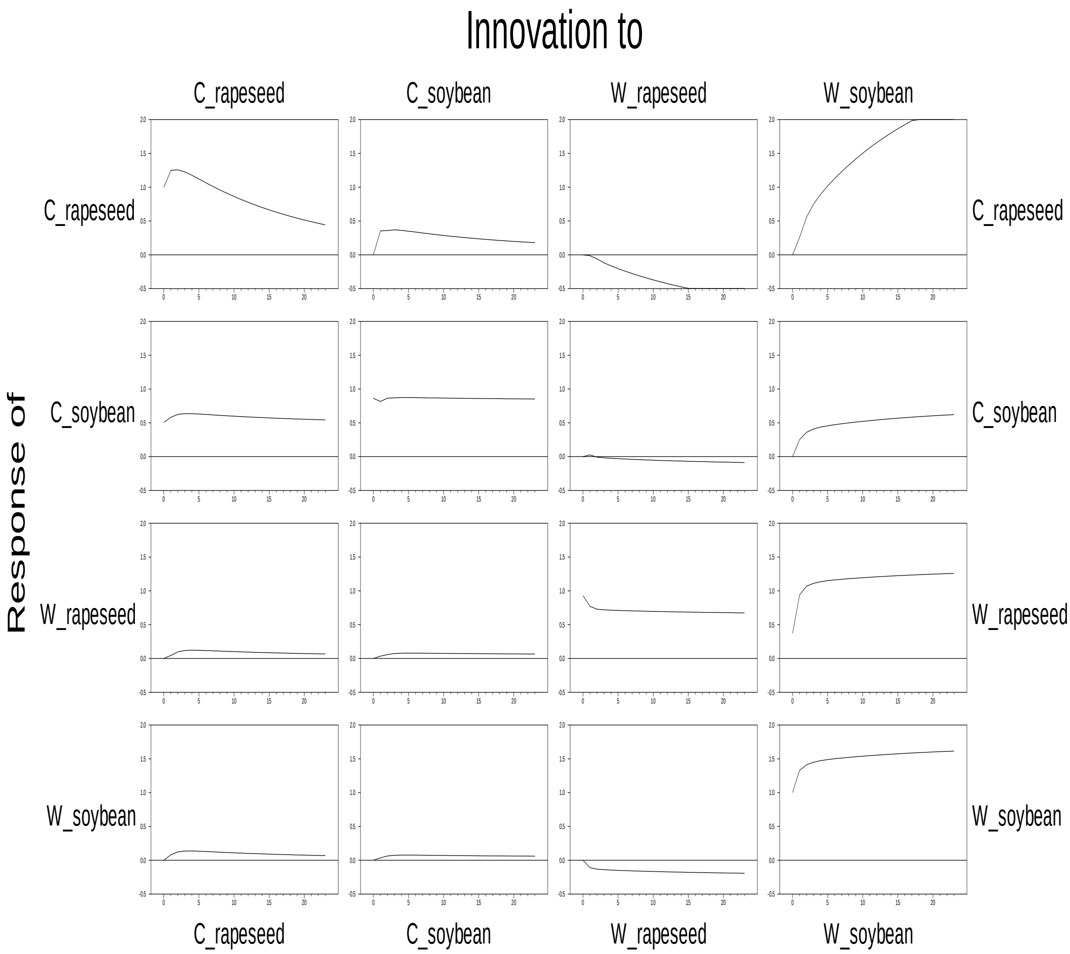

Fig.3. Impulse response functions

6. Conclusion

Below we present some preliminary as well as expected results. We found presence of unit roots (monthly) in all four price series (World and China domestic price of soybean and rapeseed oil). According to the cointegration test using two different loss metrics, the results show that there is one co-integrating vector among the variables. According to impulse responses, China rapeseed oil price responds to China soybean oil price, World rapeseed oil price, and World soybean oil price. Structural breakpoints will help delineate effects of structural breaks on dynamics of world and China vegetable oil prices. A graphical directed acyclic graph structure on innovations from ECM will help explain interactions of innovations (new information) from price variables, which in turn help generate discovery mechanism with regards to world and China vegetable oil prices.

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