Price Dynamics in Food-Energy Market in China

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Abstract

In this paper we examine price transmission for major agriculture (food) and energy products in China for the years 2004 to 2010. The Error correction model (ECM) and the directed acyclic graphs (DAG) are applied to identify price dynamics among these six variables: rice, wheat, corn, coal, crude oil and ethanol.

Our major contribution to the existing literature lies in two perspectives: 1) We firstly employ the error correction model with directed acyclic graphs to study the price dynamics in the food-energy sector in China. The advantage of this approach is that it can offer data-determined (as opposed to a subjectively-determined) pattern for the contemporaneous causal flows which are then used to conduct a more reliable innovation accounting analysis of the ECM shocks. 2) We uncover a recent price transmission among major food-energy markets in China and provide a broad understanding of price adjustments across markets. The result indicates that in the short run, crop price is driving the energy price, while in the long run, crude oil is the leading factor that drives food and other energy prices. We also find that ethanol price is neither in the long-run equilibrium nor responding to deviation from long-run equilibrium. It supports that under the current policy, Chinese government has done well to prevent the ethanol price driving up the food price. The biofuel production is not the cause of rising food price in China.

Key words: energy, food, biofuel, ethanol, error correction model, direct acyclic graph

1. Introduction

Food price around the world surged recently. Since the financial crisis in 2008, the food price raises a great concern everywhere in the world, in both developing and developed countries. Starting from the price rise of pork in 2006, the food price in China has never stopped. Although the Chinese government keeps rationing the major food prices in a reasonably range, soy beans, garlic, sugar, ginger, and egg prices have been rising sharply one after another.

Food security remains a top concern in China. To prevent possible speculation in major crops and guarantee people get fed, the price of basic food in China is under the government’s control during the period of 2007 to 2010.

The first price control measurement came up in 2007, when the Chinese government began to use its massive food reserves, which was mostly composed of grains (i.e. rice, wheat and maize). The food reserves were built to manage food shortages in case of significant nature disaster, and is extended to various part of China. The basic method of price control measures is to hold sales of surplus stocks when the food price is about to rise, usually carried out by the grain bureaus in certain counties. Given the size and price of the sales, it quickly dominates the market trading and eliminates all the possible arbitrage opportunities within PRC. Little information about the size of this nationwide food reserve system is disclosed from official sources, but media articles disclosed during the period of “Eleventh Five Year Plan” (i.e. from 2006 to

2010), the number of depository warehouses directly reporting to the central government reaches 353, with a total capacity of c. 43 million tons. But as Premier Jiabao Wen stated in March 2008, China still has around 150 to 200 million tons of grain stocks that could be used to stabilize the grain price in PRC, we inferred that his number included some of the semi-official reserve depositories which are not directly reporting to the central government but could be used to implement the reserve system when needed, which is a common practice in China.

The government also tried to import from grain exporting countries by signing long-term futures and forward contracts. But it soon became clear that in one hand the world food price is rising significantly and it would be too expensive to purchase abroad; on the other hand, being a country holding more than 20% of world population, it would be hard to purchase a meaningful amount compared to its domestic production.

In later 2007, the world food price rose so high that it became obvious to the trading companies there actually be an arbitrage opportunity to export China's food into global markets. When the first 11 months of 2007 saw an 85.3% export increase in maize and a 130% export increase in wheat together with an 85.6% decrease of imports, the government had to implement several severe measurements trying to stop grain exporting. On December 18, 2007, government cancelled the 13% export tax rebate on grains, putting an end to this export incentive policy which was introduced in 2002 by Ministry of Finance and State Administration of Taxation; on December 30, 2007, they raised export tax upon grains and grain products; only two days later on, January1, 2008, placed a quota limit on grain milling products.

The government also turned its attention to other subsidiary products in agriculture, especially fertilizer. China has made a world miracle in grain production efficiency, a miracle which is highly depends on large labor and fertilizer inputs, and that means fertilizer has a special role in China's grain production. On February 15, 2008, government raised an 35% export levy on phosphate fertilizer products till September 30, 2008, and decrease this to 20% hence; on April 20, 2008, and further raised a special 100% export levy on all fertilizer products till September 30, 2008; on August 30, 2008, a further increase of 150% export levy on all fertilizer products and would be effective till December 31, 2008.

As the world financial crisis broke out in later 2008, the food price in China became more stable, while the government was still trying to raise the "Minimum Purchase Price" on major food products. According to official number, the 2009 minimum purchase price for wheat and grain rose c.15% and c.16% compared with the 2008 price, which is the largest increase since the minimum purchase price policy was introduced in 2004. While in 2011, the minimum purchase price for wheat increased c. 8% and grain price raised c. 20% comparing with the 2010 price. At the same time, government also tried its best to import as much grains as possible. According to the General Administration of Customs, China imported 1.57 million tons of maize, 19 times the 2009 number, and 1.2 million tons of wheat, a 36% increase comparing with the 2009 figure.

Even with such price rationing in China, the food price has been raising significantly – from January 2007 to December 2008, rice, maize, and wheat prices are up 36.7%, 36% and 35.5%, respectively, while the CPI number at the same time only rose 8%.

Many studies have been conducted to examine the rising food price. Headey and Fan (2008) attempted to provide a comprehensive review of the rising international food prices based on previous studies, where they found rising oil prices, depreciation of the US dollar, biofuels demand and some commodity-specific explanations turn out to hold up much better than others, while they reject rising demand from China and India as an important cause of the crisis because both of them have long been self-sufficient in food.

There are also concerns about the role of speculators in driving up worldwide food prices. The concerns raised base on the fact that increasing financial market activity does in fact coincide with rise in food prices, and some argue that the securitization of agricultural products introduce many noncommercial participants into the trading activities. The Conference Board of Canada (CBC, 2008) provides an authoritative view. Generally speaking, speculation activity will chase after relatively mis-priced products, and higher prices will significantly reduce this (as it is today), which weakens the causality argument; and there is so far no clear evidence yet of a causal link between the higher food price and the speculative activities.

Another common argument comes from the biofuels demand. The biofuel trend has surged since 2003, there are many studies focus on the correlation of the introduction of biofuels and the rising of food prices; however most of them focus on the case of North America and Brazil, which altogether compose more than 70% of world's bioethanol production. Tokgoz, Elobeid, Fabiosa etc. (2007) examined the outlook of effects of biofuels on US grain, oilseed and livestock markets: by employing a multi-product, multi-country deterministic partial equilibrium model, they found that the expanded US ethanol production will cause long-run crop prices to increase, which would then cause livestock farm gate prices to rise. Jody, Henry, James and Joe (2007) tried to examine the evolving correspondence (covariability) between petroleum prices and agricultural commodity prices (including corn, sorghum, sugar, soybeans, soybean oil and palm oil prices) during 2003-2007, where a Johansen cointegration test shows no cointegrating relationships during 2003-2005, while corn and soybean prices were cointegrated with petroleum prices during 2006-2007. Balcombe and Rapsomanikis (2008) conducted research about nonlinear adjustment toward long-run price equilibrium relationships in the sugar-ethanol-oil nexus in Brazil, and they find that the long-run drivers of Brazilian sugar prices are oil prices and there are nonlinearities in the adjustment processes of sugar and ethanol prices to oil price but linear adjustment between ethanol and sugar prices. Serra, Zilberman, Gil and Goodwin (2008) using a smooth transition vector error correction model to assess price relationships within the US ethanol industry, they confirm the existence of an equilibrium relationship between ethanol, corn and oil prices.

Brookes, Yu, Tokgoz and Elobeid (2010) examined the production effects of the technology and impacts on cereal and oilseed markets through the use of agricultural commodity models. Their analysis suggests that world prices of corn, soybeans and canola would probably be 5.8%, 9.6% and 3.8% higher respectively than the 2007 baseline levels if the advanced production technology was no longer available to farmers.

Surprisingly, there are few empirical studies about the rising food price in China. Zhu Ling (2008) employed the sample survey data from 2006 to 2007, and found that despite the inflation of food and energy prices, consumption per capita in China is changing less than in the international market. However, in urban areas, the low income groups have been shifting their consumption of high value food to lower value substitutes. Also, rural samples shows households are reducing total consumption expenditure in real terms. She suggested implementing measures such as stopping subsidies to biofuel production and providing food aid to poor people, and employing anti-monopoly tactics and socioeconomic policy reform to adjust the social structure. Yang, Qiu, Huang and Rozelle (2008) discussed how China is being affected by and responding to the world food crisis. Through the using of a global CGE model, they show that the initial world price rise was largely due to higher world oil prices and demand for biofuels as opposed to other factors, especially in corn and soybeans. China’s response might be different, and it has kept relatively low grain prices to world grain market and to domestic soybean prices.

As far as we know, no study to date has examined interdependencies among major food prices and energy prices in China systematically, the previous studies may focus on specific crop or energy, while our study will bring all major foods and energies prices in China together and conduct a complete dynamic analysis underlying those prices.

2. Energy and Food Market in China

The introduction of biofuel in China was born with great debates. The original purpose for introducing biofuel in 2001 was to make use of the aging grain. On one hand, the government wants to step ahead on the development of biofuel, as it charts out in the “Middle and Long-Term Development Plan of Renewable Energy”, setting the goal of bioethanol production of 10 million tons by 2020, along with a set of incentive policies to support its development, i.e., government would refund 17% value added tax and 5% consumption tax on bioethanol usage. However, on the other hand, the rising food price and the general concerns that the development of biofuel would devour the crops that have already stretched has brought a quick end to the unrestrained growth of biofuel industry in China, and greatly a slowdown China’s biofuel expansion plan.

Currently, coal, crude oil and ethanol are the major consumer energy sources in China. Data from the China Statistical Abstract 2010 shows that coal and crude oil compose 87% of total energy production in China (with coal 77.2% and crude oil 10%), and from 1978 to 2009, compose an average of 91% of the total energy production in China (with coal 74.6% and crude oil 16.5%). Crude oil and its major product gasoline are the major power sources of vehicles. The introduction of ethanol to be blended with gasoline proportionately (10% ethanol with gasoline in China) would be a rather green alternative to pure gasoline, since it would significantly reduce the emission of carbon monoxide and hydrocarbons. Therefore we will include the price for coal, oil and ethanol in this study and the detailed description about the data will be given in section 4.

For the food sector in China, according to the 2010 data of Bureau of Statistics of China, during the years 1999 to 2008, grain composed at least 87% of China's food production, which consists of rice, wheat and corn, with average percentage of 34%, 19% and 25% respectively.

This study will include 6 price variables, 3 food price variables including price of rice, wheat and corn, 3 energy price variables including price of oil, coal and ethanol. For a short period, their prices may vary from each other and reflect much information about the cost and supply-demand change, but in the long run, their prices should be linked together in a cointegrated way and follow the long-run equilibrium eventually. This makes economic sense, since agricultural products and food prices have traditionally been affected by energy prices through the impact on production cost. Recently, with increasing energy prices and improved bioenergy technologies, higher energy prices are also affecting agricultural prices through increased demand for bioenergy feed stocks such as corn and wheat.

Thus, we consider using the time series approach in this study and conducting the relevant tests to identify both the long-run and short-run time properties of these variables. Empirically, the cointegration and the ECM approach have been proven very useful in accessing properties of non-stationary price series such as commodity and macro economic variables (Wilcox and Geppert 2007; Jaebeom, Masao and Yang, 2007; Mohanty, Wesley and Darnell, 1996).

In this study, we will also apply directed acyclic graphs (we will name it DAG for short thereafter) with PC algorithm in order to identify the contemporaneous causal ordering upon data-base evidence rather than a subjective-determined way. DAG reveals the causality in the contemporaneous time (innovations), and impulse responses and variance decomposition based on correct contemporaneous ordering can better show short to long run causality. As is shown by other researches, (Bessler, Yang & Wongcharupan, 2003; Yang, Guo and Wang, 2005), the method of combining the use of DAG and ECM would have better results, since the impulse response would be more reliable if the order of contemporaneous shocks are appropriately addressed.

Thus, by combining DAG methods with ECM approaches, we would be able to conduct research that would reveal the structure of long-run, short-run and contemporaneous time structure of this system, and shows a clear picture of dynamic price relationships among the major food and energy markets in China.

Our main results could be summarized as follows: Firstly, in contemporaneous timeframe, crop price plays a leading role in innovations upon other variables in the system. Secondly ethanol price is neither in the long-run equilibrium nor does it respond significantly to long-run disequilibrium, which may possibly indicate that the biofuel sector in China is still under strict regulation. Finally, we also find that oil price is affected by food price in the contemporaneous time, and it is not the major reason to explain the rising food price in China and the own and cross food prices account for larger food prices' innovations in the long run.

The remainder of the paper is organized as follows. Section 3 discusses the methodology, section 4 describes the data, and section 5 presents empirical results. Finally we offer some concluding remarks in section 6.

3. Methodology

Many macro variables and price series are proved to be nonstationary, which allows us to conduct the error correction model and use the cointegrating method to study them.

A principle feature of cointegrated variables is that their time paths are influenced by the extent of any deviation from the long-run equilibrium. The variables we include here are all basic consumer goods within the basic daily needs of common households, the rise of one variable would naturally add pressure towards another one gradually in the long run. Intuitively, within the production process of agricultural products, energy composes one of the major costs. With the rise of food price, the whole consumption level would rise and so would energy price. After all, if the system is to return to the long-run equilibrium, the movements of at least some of the variables must be related to the magnitude of the disequilibrium.

We assume that the price series of these six variables, follow a cointegration process, details of the unit root test and the cointegration test would be demonstrated in the following section. If Y_t denote a vector of nonstationary commodity prices with k being the appropriate number of lags, the data we are focusing here could be modeled in an error correction model with k lags, which is equivalent to a levels Vector Auto Regression (VAR) model with k+1 lags:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \mu + e_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \mu + e_t \quad (1)$$

$$\Pi = \alpha\beta' \quad (2)$$

In order to test restrictions on the cointegrating vector, Johansen and Juselius (1990) define the two matrices α and β, with dimension $n \times r$ and $n \times r$ respectively, where r is the rank of Π. Matrix β represents long-run cointegrating parameters, and the matrix α stands for the weights with which each cointegrating vector enters the n equations. We can view α as the matrix of the speed of adjustment parameters.

In the remaining part of the equation (1), Γ_i represents a matrix of short-run dynamics coefficients, while μ represents the time trend (constant, it may not exist for some specification), and e_t is the vector of errors (innovations). The One-step Schwarz Loss method would be employed to test if time trend exists in this model, as we will discuss that in the section 5.

More specifically, the parameters in this error correction model could be partitioned into three parts, each provides information on the long-run, short-run and contemporaneous structure of the data: long-run statistics can be examined through the hypothesis testing upon β, while the short-run structure could be identified through the hypothesis testing upon α and Γ_i. The impulse response function then could be analyzed for both short and long run dynamics.

The hypothesis test on β, or the test of exclusion from the cointegration vector is expressed as:

$$H_0: \quad \beta' = 0 \tag{3}$$

The null hypothesis is that, the i^th column of the Π matrix is zero, or i^th series is not in the long-run equilibrium (the cointegration vector). This is the same as the situation that we impose zero restriction upon each β vector.

We also interest in the hypothesis test on α, or the test of weak erogeneity for each series, which is:

$$H_0: \quad \alpha = 0 \tag{4}$$

The null hypothesis is the i^th row of the Π matrix is zero, or each series does not respond to disequilibrium among the variables. Johansen (1992) had a formal discussion about weak exogeneity.

There are three common approaches to analyze the ECM dynamic price relationship, through the innovation accounting analysis: forecast error variance decomposition, historical decomposition and impulse response functions (Sims, 1980; Lutkepohl and Reimers, 1992; Swanson and Granger, 1997). This paper would focus on the impulse response analysis and use impulse response function (IRF) to track the impact of shock on all variables within the system.

Let X_t be an r-dimensional vector series generated by

$$\begin{aligned} X_t &= A_1 X_{t-1} + \ldots + A_p X_{t-k} + e_t \\ &= \Phi(A) e_t = \sum_{i=0}^{\infty} \phi_i e_{t-i} \end{aligned} \tag{5}$$

Where $E(e_t^2) = \Sigma$, ϕ_i is the coefficients which measures the impulse response, while $\phi_{jr,i}$ identifies the response of variable j to a unit impulse in variable r occurring i^th period ago.

In most situations, covariance matrix Σ is non-diagonal; transformation would be needed to obtain the shock on one variable while others are being fixed. The Cholesky decomposition is the most common solution in this case, as Granger and Swanson (1997) and Sims (1980) pointed out, the choice or ordering in the Cholesky decomposition would have a significant impact on the impulse response function, which in turn would provide different results and explanations. The normal practice in Cholesky ordering is to impose priori contemporaneous causal relationship either by theory or some subjective judgment. Our study will use the recently developed directed acyclic graph method to solve this problem based on the properties revealed from data itself.

The directed acyclic graph is presented to allow researchers to make causal inferences from observational data (Spites, Glymour, and Scheines, 1993; Pearl, 1995; Pearl 2000; Swanson and Granger, 1997). Heretofore, it has been used for researchers to study many economic, finance and business related problems (Bessler, Yang and Wongcharupan 2003, Haigh, Nomikos, and Bessler 2004, Yang, Guo and Wang 2006, Chong, Zey and Bessler 2010). However, as recently noted by Spirtes, Glymour, and

Scheines (2000), the ability to unveil causal relationships among variables using this method is still in debate and subject to certain restrictions. It is not our purpose here to argue against those oppositions. Instead we will illustrate the use of the directed graph to identify the contemporaneous causal structure among the prices variables in food and energy sectors in China.

A directed graph is a picture communicating the causal flow among a set of variables. Lines with arrowheads are used to represent such flows; the graph $A \rightarrow B$ indicates that variable *A* causes variable *B*. Here we consider directed acyclic graphs (DAG), which means that we do not consider inference on systems such that information created in one variable (say variable *A*) passes on to other variables (*B* and *C*), but ultimately returns to its source (*A*); we do not study cyclical systems such as $A \rightarrow B \rightarrow C \rightarrow A$.

Mathematically, directed graph is designed to represent conditional independence as implied by the recursive product decomposition:

$$pr(v_1, v_2, \ldots, v_n) = \prod_{i=1}^{n} pr(v_i / \pi_i), \qquad (6)$$

In equation (6), *pr* is the probability of variables v_1 , v_2 , …, v_n. The symbol, π_i, refers to the realization of a subset of variables that precede (come before in a causal sense) v_i in order (i = 1, 2 … n). The symbol Π refers to the multiplication operator. It has been shown that there is one to one correspondence between the set of conditional independencies among variables implied by equation (6) and the graphical expression of variables in directed graph (Pearl 2000).

The basic idea of the directed graph is based on the insight of a non-time sequence asymmetry in causal relations, whereas the well-known Granger causality exploits the time sequence asymmetry and assumes that a cause precedes its associated effect (and thus an effect does not precede its cause). The Granger causality compared to the directed graph has obvious drawbacks. For example, variable *A* Granger causes variable *B* if knowledge of variable *A* and its past history help to predict variable *B*. In essence, variable *A* granger causes variable *B* is equivalent to test that variable *A* precedes variable *B* in a predictive sense. Nevertheless, as Granger himself notes, Granger causality implies temporal predictability but does not address the issue of control: “If *Y* [Granger] causes *X*, it does not necessarily mean that *Y* can be used to control *X*.” (Granger, 1980) The difference is important; because an analysis based on Granger causality can answer the question, “Does knowledge of the crude oil market help to predict the rice market?” However, it cannot answer the question “Could the government curb crude oil price to control rice price?” What Granger causality cannot do could be performed well by the directed graph. Hence we will utilize the directed graph to identify contemporaneous causality and build the error correction model to analyze the price dynamics of the food-energy market in China.

4. Data

The data from this study come from two sources. The price series for rice, corn, wheat, coal and crude oil are from the WIND database. The data series for rice, corn and wheat are collected from China Zhengzhou Grain Wholesale Market, which is the monthly national wholesale price[1]. The coal prices are Shanxi Youhun price[2]. The crude oil prices are the monthly average import price which is from General Administration of Customs[3]. The ethanol price series are from the CEIC Data, and refer to the wholesale ethanol price in China.

Figure 1 are the plots of data, notice that all the price series exhibit an upward trend in the long run, and price of crude oil records a major decline during the financial crisis period in 2008-2009, and has not reverted to its peak level before crisis to this moment.

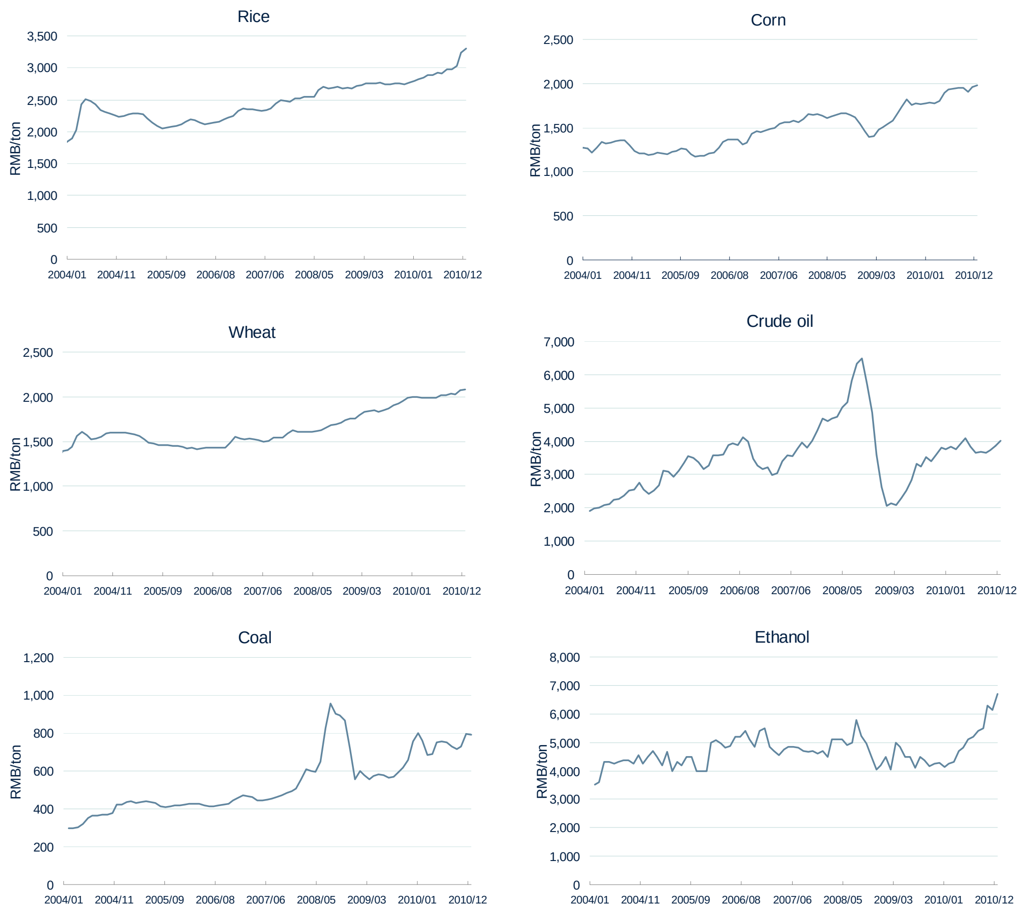

Fig.1 Price on rice, corn, wheat, crude oil,
coal and ethanol, Jan 2004 to Dec 2010

5. Empirical Results

We apply the formal unit root tests on all of the six price series. We fail to reject the null hypothesis of a unit root in each data series, and all the test statistics are listed

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[1] Early indica rice refer to the rice that first come to the market every year, it is the earliest category in rice to have traded futures market in China. No. 2 yellow corn and white wheat are the standard goods in trading activities

[2] Shanxi Youhun, is widely regarded as the representative type of its kind, and as the general indicator of China coal price

[3] The wholesale price of crude oil is commonly lagged behind the international price (i.e. import price), and since 2009, imported oil composes more than 50% of crude oil consumption in China

below in Table 1. As all the six series have a unit root, it is reasonable for us to assume that they are cointegrated and being modeled with error correction model.

Table 1. Augmented Dickey-Fuller Unit Root Test on rice, wheat, corn, crude oil, coal and ethanol with trend and intercept[4] selected

	T-Statistics	P-value*
Rice	-2.396808	0.3785
Wheat	-0.629896	0.9744
Corn	-2.424011	0.3647
Crude oil**	-2.532563	0.3121
Coal**	-2.751968	0.2193
Ethanol	-2.545511	0.3061

*MacKinnon (1996) one-sided p-values.
**We use Phillips-Perron test for crude oil and coal price since they may exhibit the structure break

The common approach to build an error correction model is to use a trace test or Akaike information criterion to determine the cointegrating rank and the lag order subsequently in two steps. We use the one step Schwarz Criterion in this paper to determine the lag order and the cointegration vectors in the error correction model simultaneously. As suggested by Wang and Bessler (2005), this method proved to be at least as well as the traditional trace test or two steps process in both consistency and efficiency.

In this paper, we check the Schwartz Loss for rank=0, 1, 2, … respectively, and each model specification by lags and locate the one that minimizes Schwartz Loss. The process then starts with lag 0 and ends at lag 12[5]. The one-step Schwarz Loss criterion suggests that the optimal model should have 1 cointegrating vector and 1 lag without deterministic trend, as shown in Table 2.

TABLE 2
One step Schwarz Criteria (SC) by Lags on the number of cointegrating vectors (*r*) and model specifications fit over the period Jan. 2004 – Dec 2010
The optimal lag and rank combination is marked in bold in the table

	Models				
Rank	No intercept No trend[1]	Intercept No trend I[2]	Intercept No trendII[3]	Intercept Trend I[4]	Intercept Trend II[5]
---Lag 1---					
0	69.30641				
1	68.75997	***68.52199***	68.73051	68.77792	68.998
2	69.13474	68.94798	69.11914	69.09332	69.26516
3	69.63852	69.39354	69.51823	69.5368	69.66428
---Lag 2---					
0	69.35988				

[4] Trend and intercept is chosen because the data plot show clear time trend and this specification supports the minimized loss criterion.
[5] Detail statistics are available from corresponding author upon request

TABLE 2
One step Schwarz Criteria (SC) by Lags on the number of cointegrating vectors (*r*) and model specifications fit over the period Jan. 2004 – Dec 2010
The optimal lag and rank combination is marked in bold in the table

	Models				
Rank	No intercept No trend[1]	Intercept No trend I[2]	Intercept No trendII[3]	Intercept Trend I[4]	Intercept Trend II[5]
1	69.04803	69.05434	69.24961	69.26944	69.41198
2	69.41383	69.46242	69.63468	69.56604	69.70335
3	69.91106	69.95087	70.07574	70.02039	70.10839
Lag 3					
0	69.80715				
1	70.51161	70.56004	70.74291	70.79297	70.82869
2	70.84994	70.88428	71.06519	70.9902	71.10963
3	71.31207	71.38019	71.51763	71.40477	71.47657
Lag 4					
0	71.24097				
1	71.85432	71.90928	72.1122	71.82353	71.96149
2	72.13161	72.20735	72.39916	72.05905	72.15685
3	71.85432	72.20735	72.39916	72.05905	72.15685
Lag 5					
0	72.42975				
1	72.88457	72.9344	73.13784	72.96765	73.08156
2	73.26549	73.15112	73.3194	73.07618	73.14935
3	73.72541	73.62306	73.74037	73.34602	73.37825

[1] Test assumes no deterministic trend in data, and no intercept or trend in cointegrating equation (CE) or test VAR;

[2] Test assumes no deterministic trend in data, have intercept (no trend) in CE, but no intercept in VAR;

[3] Test allows for linear deterministic trend in data, and assume intercept (no trend) in CE and test VAR;

[4] Test allows for linear deterministic trend in data, and assume intercept and trend in CE, but no trend in VAR;

[5] Test allows for quadratic deterministic trend in data, and assume intercept and trend in CE and linear trend in VAR.

The discovery of one cointegration relationship among these six non-stationary series supports that their dynamic trends are linked together and they may follow the same long-run equilibrium eventually. We can conduct the test and analysis then for the causal relationship within these variables in the long run so that we could find out whether the common belief that the rise of energy price is the cause of rise in food markets applies to China. The food and energy market in China is not under perfect competition and the government always tries to implement some price intervention in these two sectors. Thus we are also interested in exploring if there exist any market power such as price leadership and monopoly power in a specific market.

The error correction model is estimated as follows (t-statistics are in parentheses):

$$\begin{bmatrix} \Delta rice \\ \\ \Delta wheat \\ \\ \Delta corn \\ \\ \Delta crudeoil \\ \\ \Delta coal \\ \\ \Delta ethanol \end{bmatrix} = \alpha\beta' X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} =$$

$$\begin{bmatrix} \text{-0.1778} \\ \text{(-3.5653)} \\ \text{-0.0707} \\ \text{(-3.0622)} \\ \text{-0.0073} \\ \text{(-0.1987)} \\ \text{0.2039} \\ \text{(0.8341)} \\ \text{0.1638} \\ \text{(4.7431)} \\ \text{-0.0165} \\ \text{(-0.0462)} \end{bmatrix} \begin{bmatrix} 1 & 1.3613 & -1.3230 & 0.3373 & -2.7046 & -0.0104 & -2443.301 \\ & (4.4554) & (-7.1777) & (7.4519) & (-0.2795) & (-0.2795) & (-7.0994) \end{bmatrix} \begin{bmatrix} rice(-1) \\ wheat(-1) \\ corn(-1) \\ crudeoil(-1) \\ coal(-1) \\ ethanol(-1) \\ 1 \end{bmatrix} +$$

$$
\begin{bmatrix}
0.4606 & 0.0534 & 0.1217 & 0.5273 & 0.0269 & 1.1253 \\
(3.9520) & (0.9907) & (1.4222) & (-0.9231) & (-0.3335) & (-1.352) \\
0.6299 & 0.4569 & -0.1349 & -2.5585 & 0.0025 & -0.256 \\
(-2.3575) & (-3.6950) & (-0.6877) & (-1.9537) & (-1.0134) & (-0.1342) \\
-0.6527 & -0.1926 & 0.2666 & 0.1584 & -0.0975 & -1.2773 \\
(-3.9307) & (-2.5067) & (-2.1872) & (-0.1946) & (-0.8483) & (-1.0773) \\
0.0887 & 0.0132 & 0.0324 & 0.4597 & 0.0106 & 0.1193 \\
(-3.3549) & (-1.0763) & (-1.6716) & (-3.5494) & (-0.5777) & (-0.6322) \\
-0.2899 & 0.0268 & -0.0217 & 0.9445 & 0.3860 & -0.0813 \\
(-1.8515) & (-0.3704) & (-0.1892) & (-1.2307) & (-3.5599) & (-0.0727) \\
0.0229 & 0.0084 & 0.0168 & 0.2105 & 0.0117 & -0.2166 \\
(-1.3841) & (-1.1002) & (-1.3852) & (-2.5960) & (-1.0212) & (-1.83334)
\end{bmatrix}
\begin{bmatrix}
rice(-1) \\ wheat(-1) \\ corn(-1) \\ crudeoil(-1) \\ coal(-1) \\ ethanol(-1)
\end{bmatrix}
$$

Considering the one cointegrating vector, we then carry out the test of exclusion from the cointegrating vector according to equation (3), to identify whether each series could be omitted from the cointegrating space. The null hypothesis is that price series i are not in the cointegrating space and follow the chi square test statistics with one degree of freedom under 10% of significant level.

The result turns out that we fail to reject the null hypothesis for ethanol, and reject the null hypothesis for the rest, as is shown in Table 3. According to this result, rice, corn, wheat, coal and crude oil are all in the long-run cointegrating relations. It turns out that ethanol is not in this long-run cointegrating system and they may deviate from long run equilibrium relationship more independently, which is consistent with the fact that ethanol is a less important source in food-energy system and under strict government regulation as well in China.

We also investigated the weak exogeneity of each series relative to the long-run equilibrium according to equation (4), with the results shown in Table 3 also. We wanted to find out if each series responded to perturbations in the long-run relationship and it turns out that rice, wheat and coal respond significantly and adjust quickly to the disequilibrium while others do not.

Since ethanol is not in long-term equilibrium and it does not respond to long-term perturbations from other variables, ethanol might be quite autonomous in the long run. It is quite different from other studies (Tokgoz etc.2007, Serra etc 2008) which support ethanol prices will cause the change of crop prices or adjust to deviations from the long-run equilibrium. Moreover our test results support that corn and crude oil exhibit weak exogeneity, indicating that they might be leading variables in the long run and it is understandable since corn is the major feedstock for industry use including bioenergy, and oil is still the major energy source in agriculture.

Table 3: Test of Coefficients on the Cointegrating Space

Hypothesis	Degree of Freedom	Chi-Square Test Statistics	Decision

$\beta_1 = 0$	1	16.9083	Reject
$\beta_2 = 0$	1	12.6017	Reject
$\beta_3 = 0$	1	18.8175	Reject
$\beta_4 = 0$	1	23.0525	Reject
$\beta_5 = 0$	1	23.0844	Reject
$\beta_6 = 0$	1	0.0672	Fail to reject
$\alpha_1 = 0$	1	8.8988	Reject
$\alpha_2 = 0$	1	7.3732	Reject
$\alpha_3 = 0$	1	0.0365	Fail to reject
$\alpha_4 = 0$	1	0.4998	Fail to reject
$\alpha_5 = 0$	1	12.7853	Reject
$\alpha_6 = 0$	1	0.0020	Fail to reject

Note: Subscripts explanations as follows: 1 to 6 indicates price for rice, wheat, corn, crude oil, coal and ethanol respectively.

It is generally hard to interpret the individual coefficients of an error correction model, or the short-run coefficient and structure. In fact, it is well recognized that the innovation accounting method may be the best way of studying the dynamic structure over time. Below, the estimated correlation matrix of innovations (errors) is shown in Table 4.

Table 4: Correlation Matrix of Innovations (Errors)

	RICE	CORN	WHEAT	OIL	COAL	ETHANOL
RICE	1.0000					
CORN	0.4962	1.0000				
WHEAT	0.1010	0.3514	1.0000			
OIL	0.2166	0.1311	0.3595	1.0000		
COAL	0.1709	0.2763	0.2858	0.2110	1.0000	
ETHANOL	0.4614	0.3211	0.0262	0.2787	0.2548	1.0000

Note：Time series of errors come from ECM. Higher correlation (>0.2) of errors are treated as significant and the identification problem may be especially important (Walter Enders, Applied Econometric Time Series)

This matrix would then be used as the input for our contemporaneous causation analysis with directed graph. The result is reported below in Figure 2, where the final directed graph of the innovations of six series are plotted assuming causal sufficiency[6] with 10% of significant level (as suggested by Spirtes, Glymour, and Scheines (2000)), although we get robust results under the 5% of significant level.

[6] This assumption of causal sufficiency suggests that a sufficiently rich set of theoretically relevant variables are used for this model. According to Ministry of Agriculture (as shown in Appendix), in 2008, grains (including rice (36.3%), corn (31.4%) and wheat (21.3)) compose 90.5% of China's total food production. On the other hand, coal (77.2%), crude oil (10%) and ethanol compose most of China's energy supply. Causal sufficiency may be too strong to be satisfied in applied studies, since such studies can only involve a limited number of variables.

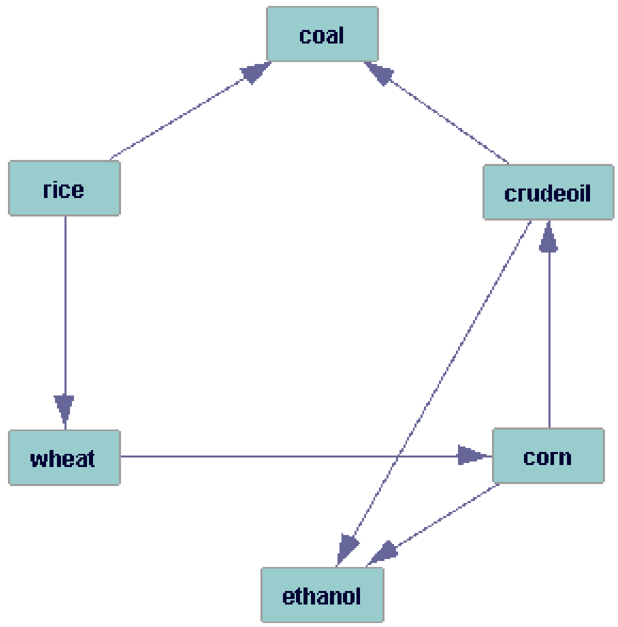

Fig. 2. Directed Acyclic Graphs on Innovations

This direct graph result is then used for determining the contemporaneous structure of these price series. As shown in Figure 2, these six variables are tightly linked together, as each of them has at least one edge with other variables. Apparently, rice starts the whole dynamic process in the contemporaneous time. Two edges are coming out from rice towards coal and wheat, while wheat then coming down to corn, which has two edges coming out from corn to ethanol and crude oil, indicating that innovations from rice drive the innovations in wheat, corn and then crude oil, who jointly drive ethanol with corn, and jointly drive coal with rice. Since ethanol is mostly produced from corn and is mixed with crude oil in practice, it is nature that ethanol is driven by corn and crude oil in contemporaneous time. Our results also cast doubt on the common belief that the price of crude oil and ethanol is the driver of food price, at least in the contemporaneous time, it is not the case. The other interesting finding is that rice, wheat, and corn are the cause of the price change of oil and coal in the contemporaneous time. It might be explained by the fact that coal or oil prices change relatively slowly compared to food price due to stricter price regulations on coal and oil. The rising food prices may already reflect the situation that will increase the energy price later.

Overall, this result indicates the contemporaneous interactions among these six variables, and rice may exhibit strong contemporaneous leading effect on other variables. Also, we discover an interesting causal relationship that it is the food price innovations that generally drive the energy price, not the other way.

With the results of the direct acyclic graph, we can determine the order of ECM shocks in the Cholesky decomposition. Such method would allow less arbitrary for the Cholesky ordering and increase the accuracy of impulse response analysis. Our practice shows that when the order of Cholesky decomposition is changed, results turn out to be significantly different.

Figure 3 below reveals the impulse response associated with our error correction model to discover the price relationship in both short-run and long-run horizon.

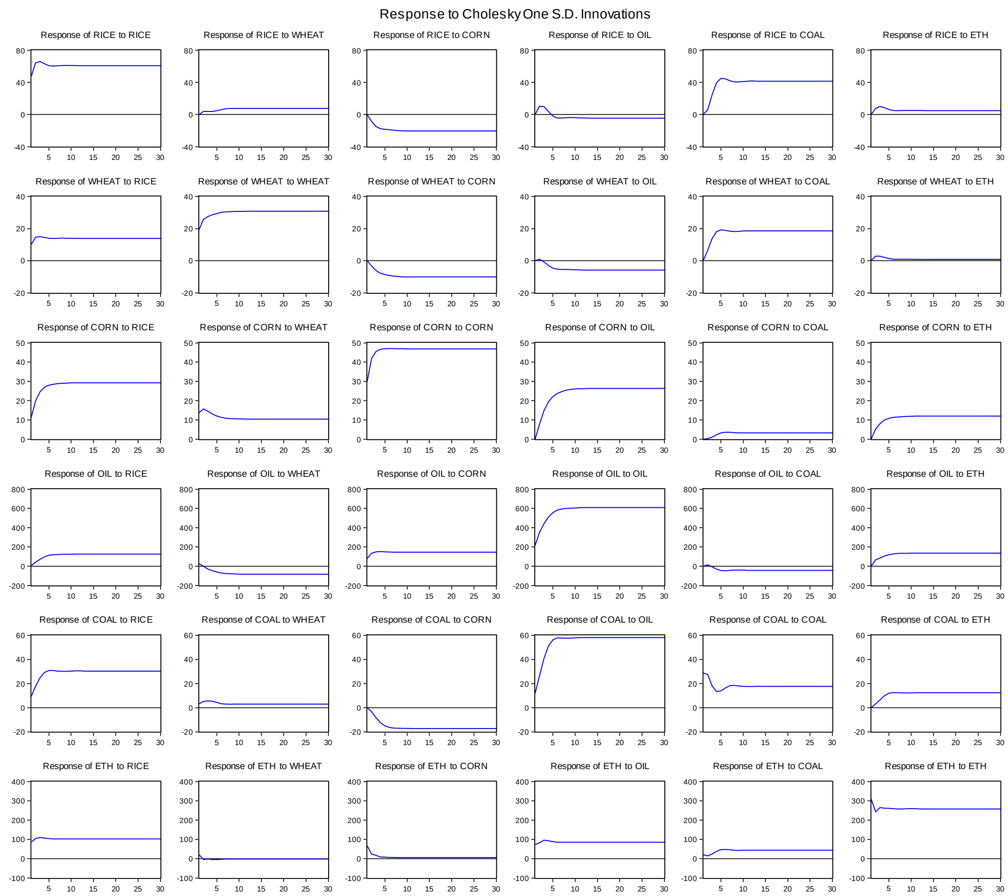

Fig. 3. Impulse responses on innovations

We notice first that, coincide with our hypothesis test results, since ethanol is not in the long-term equilibrium and hence does not respond to long-run perturbation, its own innovation accounts dominate it's response to shocks. Except for crude oil, it shows little impact upon other variables, which indicates that in the Chinese market, ethanol does not exist as a significant factor influencing food price as in the US and Brazil. In China, ethanol is generally used mixed with petroleum and used in personal vehicles, it is natural that it shows impact on crude oil.

The fact that crude oil is in the long-term equilibrium but does not respond to long-term perturbations of other variables in the system indicates that it is actually the leading variable, and it is also confirmed with the impulse response here. While the weak exogeneity for corn is not clearly supported by the impulse response here. Thus we believe oil actually has strong leading power in the long run. One needs to notice that, the impact of oil on wheat and rice in the long run is mainly through its impact on coal. As we know, food and energy systems are under strict control by the central government in China, and among them, specifically rice, wheat, and coal are traditionally decided by the government for many years, and free market practice was introduced only recently[7]. While corn, oil and ethanol prices are mainly determined by market and less by regulation. From the impulse response, we see that oil shows a significant long run impact on other variables (corn, coal and ethanol), while it does not respond significantly to all other variables. It also suggests that oil has more leading power in the long run. Oil might be a greater driving force in the energy and food sector in the long run which is consistent with previous study and common belief.

It is rather interesting to see a quite significant negative response of wheat, rice and coal in the long run to the shock of corn. We believe that this is the result of central government intervention of the market activities, since wheat, rice and coal are under strict price control, we would expect the negative response of these three to a positive shock of corn price (generally a signal of inflation) since the government tries to keep these three prices in line when facing inflation pressure. Our impulse response here may just reveal the strong market intervention in the rice, wheat and coal markets.

There is some interesting asymmetric price responses revealed from impulse response, such as the negative though insignificant response of oil to coal, positive and significant response of coal to oil. It also supports that in the long run, oil might have great power in influencing other price variables and is more fundamental to price adjustments.

We also notice rice exhibits significant influence upon other variables except oil in the long run (though there is positive impact of rice on oil in the long run, while compared to its own impact of oil it is much smaller, basically, the oil price is influenced by its own shock in the long run). Rice is the number 1 rationed good in China, and a basic component in the people's daily consumption basket. We believe that rice accounts for a significant part of China CPI, and works as the benchmark price, other prices except oil will rise alongside with it.

In sum, we find out that in contemporaneous time, the rice price is the leading factor in the system. While in the long run, oil is actually leading to other variables, though rice still shows significant power in influencing other prices except oil in the long run. We also find that ethanol does not have a significant impact upon the price of food in China.

6. Conclusion and policy implications

This paper examines dynamic price relationships in the food and energy market in China for the years 2004 to 2010 by using error correction model combined with the directed acyclic graphs. As far as we know, this study is the first one trying to uncover the dynamic relations between major food and energy products in China. Prices of rice, wheat, corn, coal and crude oil are found to be in the long-run cointegrating

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[7] The price of coal is allowed to fluctuate partly freely since 2004, but its price still under the government review; a formal document in 2009, 'Guidance to improve the production and transmission of coal', suggested to the local NDRC that more freedom should be given to the enterprises

space while the prices of ethanol are not, maybe because ethanol is still the less important energy source and its production is still insignificant in China. Furthermore, prices of rice, wheat and coal are found to be responsive to perturbations (shocks) from our long-run equilibrium, while corn and crude oil do not respond to such shocks indicating the weak exogeneity for corn and crude oil in the long run.

We also find strong contemporaneous correlations among the innovations from our error correction model. We employ DAG methods to examine contemporaneous causal relationships among price series investigated. The use of DAG to examine the contemporaneous causal flows turns out to be very useful, since it provides data determined but not subjectively-determined evidence for the ordering of shocks in the Cholesky decomposition which is the base to obtain the accurate impulse response. Our practice also supports that the ordering of shocks really has great impact on the impulse response result.

We find that in contemporaneous time, rice is the main initiator of innovations and coal and ethanol are the most influenced variable in contemporaneous time.

Our study shows that ethanol has little impact on other variables in the system, and remains mostly unaffected by other variables. Although the government has made it's effort to introduce ethanol into the current fuel system, with the national standards and three amendments announced, our study shows that at least in the current situation, ethanol does not play an important role in the current food and energy market. The concern for bioenergy production in China for "competing with grain over land, competing with consumers for food, competing with livestock over feeds" should be relieved.

Crude oil is still found to be the leading factor in the food-energy system. The oil price itself is very sensitive and may reflect much useful information regarding the economy, inflation, expectation etc, so in the very short run, oil price is affected by many other prices including major food prices. While in the long run, as the fundamental energy price, oil price influences back flow to major crop prices and other energy prices.

The above findings have important policy implications.

Firstly, our study shows that in the very short-run (i.e. 0 to 1 month), crop prices like rice price cause the change in energy price, not the opposite way commonly believed. This relieves the worry that the crude oil price, which is mostly determined by the world market since China has not sufficient domestic supply for oil and relies heavily on imports, may have a direct effect on China food price, and foreign speculation on oil may endanger the food security in China in the short run. While in the long run, oil price is still the leading factor that drives the food prices and other energy prices, thus to guarantee future energy and food security, China should aim to develop more renewable energy and strengthen self food supply.

Secondly, the fact that ethanol is neither in the long-run cointegrating relationship nor responding to deviations from the long-run equilibrium indicates that the ethanol does not play an important role in energy production and food market in China currently. Government does not need to worry that the biofuel production may cause the rise of food price and endanger the food security in China.

There are some interesting questions suggested by the results that are not addressed explicitly in this paper but are important issues in the food and energy industry. Why there is asymmetric price transmission in the different markets? What is the impact of deregulation on prices? These questions should be topics of further study.

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