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A Hybrid Neural Network Method for Detecting Structural Change in Oil-Bioenergy Crops Prices System

[1]Yu Zhao, [2]Yu Zhang and [2]Hong Xu
[1]Department of Business and Management,
East China Institute of Technology, Fuzhou, 344000, China
[2]Research Center of Geological Resource Economics and Management,
East China Institute of Technology, Fuzhou, 344000, China

Abstract: The present study detects the structural change in oil-bioenergy crops prices system before and during the food crisis of 2007/2008 and financial crisis 2008/2010. In the recent years, rising world crude oil prices lead to increase of bioenergy production around the world. Bioenergy, in turn, affects bioenergy crops price, because it uses these commodities as inputs. We develop a hybrid neural network approach which can test the structural change of the linkages without priori knowledge of the input data distribution. And then we studies price linkages applying the hybrid neural network to two major bioenergy crops prices, including Argentina corn and Brazil soybean, along with two major crude oil price, including West Texas and Brant crude oil. The data consists of 1467 observations from January 2006 to November 2011. The empirical findings confirm that the structures of oil-bioenergy crops prices system change observably during the food crisis and the financial crisis.

Keywords: Bioenergy crops, crude oil, economic system, hybrid neural network, prices, structural change

INTRODUCTION

In recent years the production of bioenergy has increased dramatically around the world. The linkages between bioenergy crops and crude oil markets may be rather close, since bioenergy crops are the raw material for the production of bioenergy and the bioenergy is a substitute of the fossil energy. The prices of crude oil and agricultural commodities are not issues isolated from each other and they are interdependent (Ciaian and Kancs, 2011). Actually, the relationship between them becomes closer due to biofuels (Guo *et al*., 2012).

The similar increase in price volatility on crude oil and bioenergy crops markets raises the question about the links between crude oil and bioenergy crops prices. What’s the relationship between them? There are more and more scientific studies attempting to explain the linkages between fossil energy and bioenergy crops prices. Pindyck and Rotemberg (1990) introduce the Excess Co-movement Hypothesis (ECH) between commodity prices, arguing that due to herd behavior in financial markets the prices tend to move together. Many econometric models, including cointegration analysis and error correction model were used to estimate the relationship between the fuel price and agricultural commodities prices (Yu *et al*., 2006; Campiche *et al*., 2007; Harri *et al*., 2009; Peri and Baldi, 2010; Serra, 2011; Esmaeili and Shokoohi, 2011). Deb *et al*. (1996) find weak evidence of excess co-movement within the framework of univariate and multivariate GARCH models. Cashin *et al*. (2009) use concordance correlation to confute ECH. Ai and Chatrath (2006) use quarterly inventory and harvest data for wheat, barley, corn, oats, and soybeans, from January 1957 to September 2002 to fit a partial equilibrium model. The main shortcomings of these reduced-form empirical studies are that they do not take into account the structural change of the prices system.

Some research test structural change in the prices system via statistical methods. Peri and Baldi (2008) utilized threshold cointegration analysis to investigate if asymmetric dynamic adjusting processes exist among rapeseed oil, sunflower oil, soya oil and diesel prices in the European market. Ubilava and Holt (2009) estimated a system for vegetable oil prices by using a Smooth Transition Vector Error Correction Model (STVECM) to analyze impacts of El Nino events on production and their asymmetric nature. Balcombe and Rapsomanikis (2008) found nonlinear price adjustment in the Brazil ethanol market, using a Threshold Vector Error Correction Model (TVECM). Natanelov *et al*. (2011) employed threshold cointegration and causality tests to research on price co-movement between crude oil futures and a series of agricultural commodities and gold futures and their results indicate that co-movement was a dynamic concept and that some economic and policy development might change the relationship between commodities The main shortcomings of these empirical studies are that statistical

Corresponding Author: Yu Zhao, Department of Business and Management, East China Institute of Technology, Fuzhou, 344000, China

methods of structural change detection require priori knowledge such as the distribution of the data. But a priori is not necessarily true.

In this study, we explore structural change in the prices system employing neural network approach. Although the neural network theories have been developed rapidly, applications in this area are still few and there are a number of extensions that have yet to be investigated. Our hybrid neural network is an artificial intelligence method. And no priori knowledge of the input data distribution is needed for detecting structural change of the prices system.

The study is structures in the following manner. In the methods and data section we discuss the techniques used in our analysis. Consequently, data construction and the rationale behind the selected time periods are presented. In the following section we present and discuss the results. In the final part concluding remarks and recommendations are offered.

MODEL AND DATA

Hybrid Neural Network: Most of the methods involving structural change detection in the classic econometrics are parameter models. We have to give the hypothesis that the parameter model is linear or nonlinear. We also need to assume the nature of the parameters and the data distribution in the classic econometrics. But in practical purposes most of the time, we don't really understand enough about priori knowledge. To detect the structural change in oil-bioenergy crops prices system, the neural network may well be the most powerful tool. We developed a hybrid neural network composed mainly of a Self-Organizing Feature Map neural network and an Adaptive Resonance neural network. It is a nonparametric method which does not require the priori knowledge about the nature of the parameters and the data distribution. All rules are self-created, and they grow automatically with more incoming data.

It works the following way (Sun and Zhang, 2000) as follows:

Step 1: Standardize and normalize the raw data to make sure that the same type of data has same calibration, and set the length of the sliding window and the sliding distance at a time.

Step 2: Input the preprocessing data to Self-Organizing Feature Map (SOFM) neural network, and train the neural network via Kohonen algorithm. Repeatedly learning from sliding window samples, the SOFM network can get a stable weight matrix series including important information about structural change of the sliding window samples.

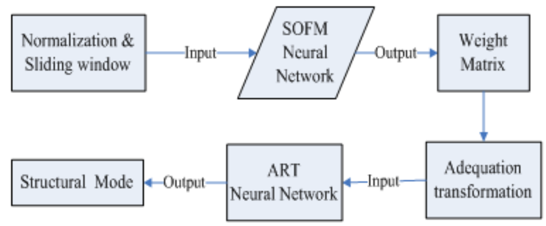

Fig. 1: Flow chart of hybrid neural network model

Step 3: Adequation transformation is used to transform all n×m matrixes into column vectors with n×m components.

Step 4: Input the vectors into Adaptive Resonance neural network. Each input vector is presented to the network one at a time. Then train the neural network via Adaptive Resonance Theory (Carpenter and Grossberg, 1987). The outputs of the Adaptive Resonance neural network are the modes of price systems. Figure 1 gives the flow chart of hybrid neural network.

Through debugging, We set the parameter of the network as follows, N1 which is the length of sliding window is 5, and the sliding length each time is 1.The number of input Kohonen neurons is 2 and the number of output Kohonen neurons is 4. The initial learning rate of SOFM neural network is 0.8 and the maximum number of training is 50; the initial learning rate of ART neural network is 0.8; the number of input node of ART is 8 and output node of ART is 3; the vigilance parameter is 0.7.

Data: Our data consists of daily price observations for WTI (abbr. West Texas intermediate) crude oil, Brent crude oil, FOB (abbr. free on board) Paraagua Brazil soya and Argentina export corn between January 2006 and November 2011. There are 1467×4 daily observations in total (Fig. 2 and 3). The data set used is daily price data obtained from Zhen Zhou Commodities Exchange Database. The descriptive statistics of variables are given by Table 1.

Table 1: Descriptive statistics of variables

	Braz Soya	Arg Corn	WTI Oil	Brent Oil
Mean	387.0177	188.9741	78.3693	80.6415
Median	394.3800	172.0000	75.3900	75.8500
Maximum	610.0000	328.0000	145.3100	143.000
Minimum	213.0500	99.0000	30.2800	34.0800
Std. Dev.	101.7461	56.6011	20.2358	22.7604
Skewness	-0.1854	0.7010	0.6267	0.5150
Kurtosis	1.8903	2.6510	3.6132	2.5311
Obs.	1467	1467	1467	1467

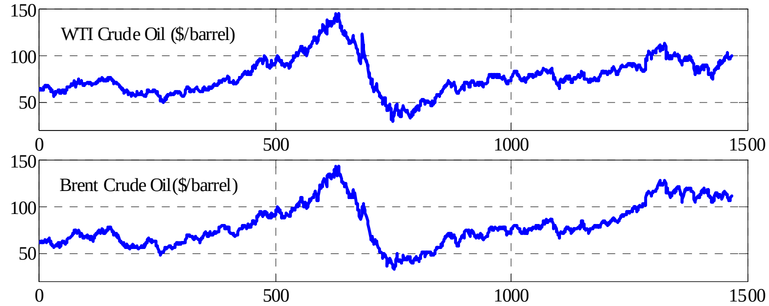

Fig. 2: Prices tendency of the Crude Oil

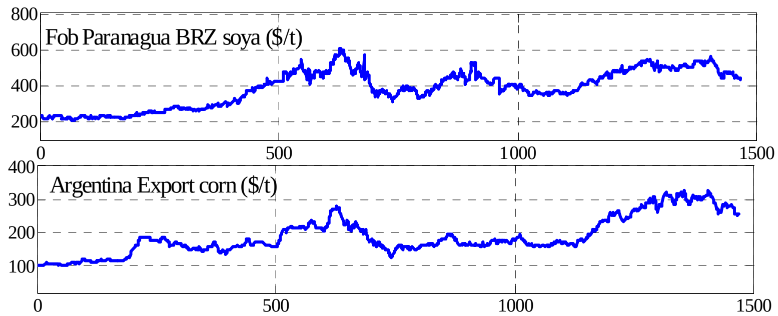

Fig. 3: Prices tendency of the bioenergy crops

RESULTS

The outputs were showed in the following figures. According to the outputs of the Hybrid neural network, the structural changes and some jump points in oil-bioenergy crops price systems were detected. Fig. 3 to 6 showed the mode change of the prices linkages. Two breaking points divided the linkages of prices series into three sample periods in WTI Oil-Brazil Soya price system: 1/31/2006 to 9/18/2008, 9/19/2008 to 8/25/2010 and 8/26/2010 to 11/29/2011. One breaking point divided the linkages of prices series into two sample periods in WTI Oil- Argentina corn price system: 1/31/2006 to 1/21/2010 and 1/22/2010 to 11/29/2011. Three breaking points divided the linkages of prices series into four sample perios in Brent Oil-Brazil Soya price system:

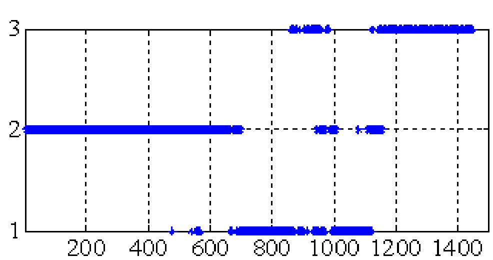

Fig. 4: Structural change in WTI oil-Brazil Soya price system

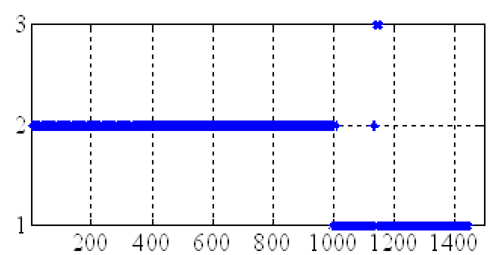

Fig. 5: Structural change in WTI Oil- Argentina Corn price system

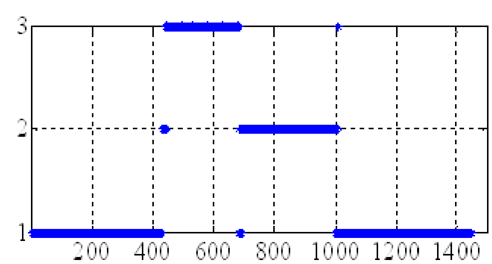

Fig. 6: Structural change in Brent Oil-Brazil Soya price system

1/31/2006 to 10/10/2007, 10/11/2007 to 10/20/2008, 10/21/2008 to 5/2/2010 and 2/8/2010 to 11/29/2011. One breaking point divided the linkages of prices series into two sample periods in Brent Oil- Argentina corn prce system: 1/31/2006 to 2/11/2008 and 2/12/2008 to 11/29/2011.

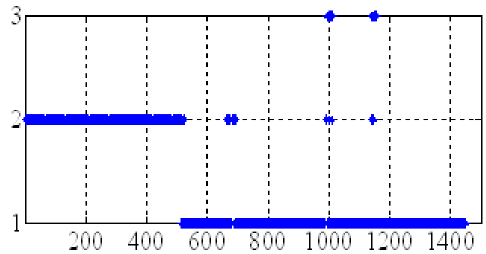

Fig. 7: Structural change in Brent Oil - Argentina Corn price system

The data split was based on the structural changes in oil-bioenergy crops price systems. Interestingly, one structure mode seemed to persist for some period of time as shown. In addition, there exist a few jump points in systems (Fig. 4, 5, 6 and 7).

CONCLUSION

Some significant international events such as war, widespread famine or financial crisis may change the structure of the price systems. The structural changes in oil-bioenergy crops price systems are observable during the food crisis 2007/2008 and the financial crisis 2008/2010 as shown. Ciaian and Kancs (2011) divided the price series into three equal samples based on the production, demand and policies for oil, bioenergy and agricultural commodities in their research. But this data split was based on subjective experience. The data split in our research, by contrast, was reasonable and objective.

To detect the structural change in financial system whose components are of long memory, Sun *et al*. (2003) developed a recursive genetic programming method and apply it to detect structural change in multivariate nonlinear time series. Comparing our hybrid neural network with recursive genetic programming method, the hybrid neural network can detect different types of the structures in the price systems and make clustering on different synergy patterns. However, the recursive genetic programming method can only detect the change points.

In addition, we discovered that jump points in time series had a bad effect on the training of the hybrid neural network in our experimental process. The larger the number of jump points is, the longer the network trained before it achieving stability. To eliminate or reduce the influence of jump points, you can increase the learning rate or extend training time, but the feasible method is filtering the input data. Combining wavelet transform with the hybrid neural network may be a good idea. It is just what we are researching on.

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