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Cross-correlations between crude oil and agricultural commodity markets

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HIGHLIGHTS

- Cross-correlations between oil and agricultural markets are studied.
- Return cross-correlations are significant for larger lag lengths.
- Volatility cross-correlations are significant for each lag length.
- Cross-correlations are weak but significant.
- Oil price increases partly contribute to food crisis in 2006–mid-2008.

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ABSTRACT

In this paper, we investigate cross-correlations between crude oil and agricultural commodity markets. Based on a popular statistical test proposed by Podobnik et al. (2009), we find that the linear return cross-correlations are significant at larger lag lengths and the volatility cross-correlations are highly significant at all of the lag lengths under consideration. Using a detrended cross-correlation analysis (DCCA), we find that the return cross-correlations are persistent for corn and soybean and anti-persistent for oat and soybean. The volatility cross-correlations are strongly persistent. Using a nonlinear cross-correlation measure, our results show that cross-correlations are relatively weak but they are significant for smaller time scales. For larger time scales, the cross-correlations are not significant. The reason may be that information transmission from crude oil market to agriculture markets can complete within a certain period of time. Finally, based on multifractal extension of DCCA, we find that the cross-correlations are multifractal and high oil prices partly contribute to food crisis during the period of 2006–mid-2008.

1. Introduction

Oil price surges in recent years inspire people to develop the alternative energy. The bioethanol and biodiesel extracted from corn and soybean, respectively, are considered as the appropriate substitutes of crude oil. Thus, increases in oil prices can result in the increases in corn and soybean prices and finally lead to the increases in prices of other agricultural commodities as the planting acreage is limited in a certain period of time. Additionally, higher crude oil prices will lead to higher production costs. In this sense, people suspect that large increases in agricultural commodity prices in 2006–2008 may be caused by rising crude oil prices [1–3]. As a response of higher oil prices, the central banks will adjust the interest rate [4,5] which may also lead to changes in commodity prices according to the standard theory of cost carry.

In this paper, we will investigate the cross-correlations between crude oil and agricultural commodity markets. The investigation of related issue can be seen in a plenty of recent studies and their conclusions are mixed. Some researchers show

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the significant oil–agricultural commodity price relationships. For example, Mitchell [3] finds that energy price contribute 15%–20% of total cost of the US agriculture. Hence, the food crisis in 2006–2008 is partly due to persistent increases in oil prices. Harri and Hudson [6] find that crude oil market volatility spills over corn futures market. Harri et al. [7] investigate the cointegration between oil and primary agricultural commodity prices. They show that corn, cotton and soybean prices are significantly correlated with oil prices. Nazlioglu et al. [8] consider that volatility spillover from oil market to agriculture market is significant only after the food crisis. This finding is further supported by Du et al. [9] in the framework of a bivariate stochastic volatility model and by Ji and Fan [10] based on a bivariate EGARCH model. Some economists document that oil–agricultural commodity price linkages are not significant. For example, Nazlioglu and Soytas [11] find that the response of Turkish agriculture price to oil price changes is not significant. Reboredo [12] finds that the tail dependence between oil and agriculture returns is very weak. Gilbert [13] shows that oil price changes do not Granger cause agriculture price changes.

A major limitation in existing studies is that they investigate the return or volatility relationships in a linear framework.[1] As the nonlinearity in asset prices and volatilities has been generally accepted [14], it is more appropriate to investigate the relationships between crude oil and agricultural commodity markets in a nonlinear framework. In this paper, we will fill this gap and do it from a completely fresh perspective. We borrow the methods from statistical physics and therefore in the area of econophysics our work is the first that investigates oil–agriculture price linkages.

In this paper, we analyze nonlinear cross-correlations between crude oil and agricultural commodity markets. Although cross-correlations in financial markets have been detected in many studies [15–20], to the best of our knowledge the cross-correlations between crude oil and agricultural commodity markets have not been investigated in existing studies.

Our empirical procedure contains four main steps. First, using a statistical test proposed by Podobnik et al. [21], we qualitatively examine whether the linear cross-correlations between crude oil and agricultural commodity markets are significant. Our results show that at smaller lag lengths, the return cross-correlations are not significant and at larger lag lengths, the return cross-correlations are significant at 10% level. The volatility cross-correlations are highly significant at each of the lag lengths under consideration. Second, we use a detrended cross-correlation analysis (DCCA) proposed by Podobnik and Stanley [22] to analyze nonlinear cross-correlations. We find that return cross-correlations are persistent for corn and soybean and anti-persistent for oat and wheat. The volatility cross-correlations are strongly anti-persistent. Third, we use a cross-correlation coefficient proposed by Zebende [23] and find that the cross-correlations are weak but significant for smaller time scales. For larger time scales, the cross-correlations are not significant. The reason may be that the information transmission from crude oil market to agriculture markets completes within a certain period of time. Finally, we use the multifractal form of DCCA [24] and find that both return and volatility cross-correlations are multifractal. By analyzing the cross-correlations during the period of recent food crisis, we find that high oil prices adequately contribute to increases in agriculture prices during the period from 2006 to mid-2008. We also give some economic and modeling implications based on the empirical findings.

The remainder of this paper is organized as follows. Section 2 gives a description of methodology. Section 3 shows data and some preliminary analysis. Section 4 shows empirical results. Section 5 is some relevant discussions. Section 6 concludes.

2. Methodology

In earlier years, cross-correlation function was always applied to dynamic systems. This method has two major disadvantages. First, it is not suitable for nonstationary time series or fat-tail distributed series. As an important stylized fact, financial time series are always long-range auto-correlated [25–27], fat-tail distributed and have strong trends. Second, this method can be used to reveal linear cross-correlations, but for nonlinear ones it is helpless. It has been generally accepted that nonlinearity widely exists in financial markets [14]. Fortunately, the detrended cross-correlation analysis (DCCA) proposed by Podobnik and Stanley [22] can overcome the drawbacks of cross-correlation function and is a robust method of detecting cross-correlations between two time series. DCCA has been widely used to detect cross-correlations [15–19,28]. It can be described as follows:

Step 1. Consider spot and futures return series used in this paper, $\{x_t, t = 1, \ldots, N\}$ and $\{y_t, t = 1, \ldots, N\}$, where N is the equal length of these two series. Then, we describe the "profile" of each series and get two new series, $xx_k = \sum_{t=1}^{k}(x_t - \bar{x})$ and $yy_k = \sum_{t=1}^{k}(y_t - \bar{y})$, $k = 1, \ldots, N$.

Step 2. Divide both profiles $\{xx_k\}$ and $\{yy_k\}$ into $N_s = \mathrm{int}(N/s)$ nonoverlapping segments of equal length s. Since the length N of the series is often not a multiple of the considered time scale s, a short part at the end of each profile may remain. In order not to disregard this part of the series, the same procedure is repeated starting from the opposite end of each profile. Thereby, $2N_s$ segments are obtained together. We set $10 < s < N/5$.

Step 3. We calculate the local trends $\widetilde{xx}_{(\lambda-1)s+j}$ and $\widetilde{yy}_{(\lambda-1)s+j}$ for each of the $2N_s$ segments by a least-square fit of each series. Then determine the co-moved variance

$$F^2(s, \lambda) \equiv \frac{1}{s}\sum_{j=1}^{s}[xx_{(\lambda-1)s+j} - \widetilde{xx}_{(\lambda-1)s+j}][yy_{(\lambda-1)s+j} - \widetilde{yy}_{(\lambda-1)s+j}] \tag{1}$$

[1] One may point out that the EGARCH model used in existing studies takes into account the nonlinear relationships. Actually, the relationship captured by EGARCH is a linear one in each of two different regimes.