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Cross-correlation between interest rates and commodity prices

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HIGHLIGHTS

- Investigate cross-correlations between interest rate and agricultural commodity markets.
- The cross-correlations are all significant and persistent.
- We find strong multifractality in both auto-correlations and cross-correlations.
- The time-variation property of cross-correlations is also revealed.

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ABSTRACT

In this paper, we investigate cross-correlations between interest rate and agricultural commodity markets. Based on a statistic of Podobnik et al. (2009), we find that the cross-correlations are all significant. Using the MF-DFA and MF-DXA methods, we find strong multifractality in both auto-correlations and cross-correlations. Moreover, the cross-correlations are persistent. Finally, based on the technique of rolling window, the time-variation property of cross-correlations is also revealed.

1. Introduction

Interest rate and commodity price can affect each other in the economic sense. On one hand, interest rate is one of the major determinants of agricultural commodity prices. According to the standard cost of carry theory, higher interest rate will improve the requirements for the future benefit from commodity storage, leading to decreases in spot prices [1]. On the other hand, the usefulness of commodity prices in formulating monetary policy has also been well documented in the literature [2–4]. The reason is that commodity markets are informationally efficient, respond quickly to general economic conditions and thereby can provide instantaneous information about the state of economy. Additionally, many commodities are also the important inputs of industry production. Therefore, increases in commodity prices can result in higher manufactured goods and finally cause the general inflation [5].

In the literature, the relations between commodity price and the interest rate are always investigated based on the vector autoregressive (VAR) model or the vector error correction (VEC) one [6–10]. Both VAR and VEC assume the linear joint dynamics as they are actually the standard regressions with the lagged variables. According to the arguments in the econophysics studies, the linkages among economic variables are intrinsically nonlinear and change over time [11–19]. Thus, it is less appropriate to capture their joint dynamics using linear specifications. Unfortunately, nonlinearity in the relations

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between commodity price and the interest rate has not been addressed in the literature. Moreover, it is well known that due to business cycles and some extreme events, the relations among different economic variables are not constant, but change over time. The existing studies have not documented the time variations in the linkages between agricultural commodity price the interest rate. Our focus is to fill these gaps.

We start from fresh perspectives in investigating the relationships between commodity price and the interest rate. First, we employ a simple but very powerful statistical test of Podobnik et al. [20] to qualitatively examine whether their cross-correlations are significant. Second, we use a method borrowed from statistical physics to investigate the long-range cross-correlations. This multifractal detrended cross-correlation analysis (MF-DXA) [21], a multifractal generalization of the seminal DXA firstly developed by Podobnik and Stanley [22], has been considered as a powerful tool in analyzing nonlinear cross-correlations in nonstationary time series. Recently, MF-DXA is also widely applied to finance researches [23–25]. Third, we use a rolling window method to investigate the evolution of cross-correlations over time.

We use the daily data of effective Federal Funds rate and four major agricultural commodity prices (corn, soybean, wheat and rice). We find that the cross-correlations are significant at 10% significance level for greater lag orders. The results based on MF-DXA indicate that the cross-correlations are persistent and multifractal. The degrees of persistence and multifractality differ depending on the type of commodity. The evidence based on rolling window method reveals the significant time-varying property in cross-correlations.

The remainder of this paper is organized as follows. Section 2 provides the description of methodologies used in current paper. Section 3 contains data. Section 4 lists the main empirical findings. In Section 5, we perform some meaningful discussions. The last section concludes the paper.

2. Methodology

Let us briefly introduce the MF-DXA method [21]. Assume that there are two series $x(i)$ and $y(i)$ $(i = 1, 2, \ldots, N)$, where N is the equal length of these two series.

Step 1. Construct the profile

$$X(i) = \sum_{t=1}^{i}(x(t) - \bar{x}), \qquad Y(i) = \sum_{t=1}^{i}(y(t) - \bar{y}) \tag{1}$$

where $\bar{x}$ and $\bar{y}$ denote the average of the two whole time series $x(i)$ and $y(i)$.

Step 2. The profiles $X(i)$ and $Y(i)$ are divided into $N_s = [N/s]$ non-overlapping windows (or segments) of equal length s. Since the length N is not always a multiple of the considered time scale s. In order to not discard the section of series, the same procedure is repeated starting from the opposite end of each profile. Thus, $2N_s$ non-overlapping windows are obtained together.

Step 3. The local trends $X^{\nu}(i)$ and $Y^{\nu}(i)$ for each segment ν $(\nu = 1, 2, 3, \ldots, 2N_s)$ are evaluated by least squares fits of the data, then the detrended covariance is determined by

$$F^2(s, \upsilon) = \frac{1}{s}\sum_{i=1}^{t}|X((\upsilon - 1)s + i) - X^{\upsilon}(i)| \bullet |Y((\upsilon - 1)s + i) - Y^{\upsilon}(i)| \tag{2}$$

for each segment ν, $\nu = 1, 2, \ldots, N_s$ and

$$F^2(s, \upsilon) = \frac{1}{s}\sum_{i=1}^{t}|X(N - (\upsilon - N_s)s + i) - X^{\upsilon}(i)| \bullet |Y(N - (\upsilon - N_s)s + i) - Y^{\upsilon}(i)| \tag{3}$$

for each segment ν, $\nu = N_s + 1, N_s + 1, \ldots, 2N_s$. Then the trends $X^{\nu}(i)$ and $Y^{\nu}(i)$ denote the fitting polynomial with order m in each segment ν (conventionally called MF-DXA-m [26]).

Step 4. qth-order the fluctuation function as follows.

$$F_q(s) = \left[\frac{1}{2N_s}\sum_{\nu=1}^{2N_s}[F^2(s, \nu)]^{q/2}\right]^{1/q}. \tag{4}$$

If $q \neq 0$, then

$$F_0(s) = \exp\left\{\frac{1}{4N_s}\sum_{\nu=1}^{2N_s}\ln[F^2(s, \nu)]\right\}. \tag{5}$$

When $q = 2$, MF-DXA is the standard of the DXA.

Step 5. Analyze the scaling behavior of the fluctuations by observing log–log plots $F_q(s)$ versus s for each values of q. If the two series are long-range cross-correlated, $F_q(s)$ will increase for values of s, we can obtain a power-law expression

$$F_q(s) \sim s^{H_{xy}(q)}. \tag{6}$$