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Cross-correlations between crude oil and exchange markets for selected oil rich economies

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HIGHLIGHTS

- Cross-correlations between crude oil and five FX markets are investigated.
- The results from cross-correlation statistics and coefficients confirm the existence of cross-correlations.
- Strong multifractality between crude oil and selected FX markets is found in both short- and long-terms.
- With rolling window analysis, we find that cross-correlations between crude oil and FX markets are persistent.
- Cross-correlation scaling exponents exhibit volatility due to its sensitivity to sudden events.

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ABSTRACT

Using multifractal detrended cross-correlation analysis (MF-DCCA), this paper studies the cross-correlation behavior between crude oil market and five selected exchange rate markets. The dataset covers the period of January 1,1996 – December 31,2014, and contains 4,633 observations for each of the series, including daily closing prices of crude oil, Australian Dollars, Canadian Dollars, Mexican Pesos, Russian Rubles, and South African Rand. Our empirical results obtained from cross-correlation statistic and cross-correlation coefficient have confirmed the existence of cross-correlations, and the MF-DCCA results have demonstrated a strong multifractality between cross-correlated crude oil market and exchange rate markets in both short term and long term. Using rolling window analysis, we have also found the persistent cross-correlations between the exchange rates and crude oil returns, and the cross-correlation scaling exponents exhibit volatility during some time periods due to its sensitivity to sudden events.

1. Introduction

As the key resource of energy for the industrialized nations, crude oil plays a pivotal role in almost all productive activities and will likely remain so for years to come. Indeed, the past decades have evidenced the continued importance of industries that are dependent on oil, and the increased impact of oil price variations on the global economy even in the wave of optimism about the growth in alternative energy sources.

In today's international energy markets, crude oil is undoubtedly one of the most-traded commodities. As US dollar denominated commodity, crude oil price often loses its ground in home currencies of all other countries, especially for

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the oil rich nations when the US dollar is strong, and vice versa. The ever-changing exchange rate accounts for part of the fluctuations of the trading volume of crude oil. Thus, understanding the dynamics of the cross-correlations between currency exchange rate and crude oil is essential for both investors and policy makers.

In recent years, considerable amount of research based on the efficient market hypothesis (EMH) has emerged on the pricing behavior of crude oil and exchange rate [1,2]. According to the efficient market hypothesis, the price volatility obeys a random walk and is subject to Gaussian distribution, and the returns resemble a white noise process. The efficient market hypothesis suggests that the future price is unpredictable, due to a lack of relation between historical prices and future prices. This can be inconsistent with the actual situations of the market, in particular when the price return displays a fat-tail distribution rather than a Gaussian distribution, or the price is persistent with some level of predictability.

This paper attempts to address two important issues. First, whether there exists cross-correlations between oil and exchange rate markets; Second, whether the cross-correlations display multifractal patterns in short term and long term. To this end, the theories and models based on the efficient market hypothesis (EMH) are not suitable for our analysis.

Hurst's [3,4] rescaled range analysis (R/S) based on Mandelbrot [5] became an increasingly popular method for the analysis of fractals, however, Lo [6] found that R/S method is likely to cause bias error due to its sensitivity to short-range dependence. To differentiate local patchiness from long-range correlations and adequately count for long-range correlations, Peng et al. [7] proposed detrended fluctuation analysis (DFA). Since Peng et al., many studies have employed MF-DFA method to explore multifractal properties in the crude oil market [8–10] and exchange rate market [11]. More recently, detrended cross-correlation analysis (DCCA) was developed by B. Podobnik et al. [12] to investigate the long range cross-correlations between two non-stationary time series, and this method has been applied to various analyses [13,14].

By combining DCCA and MF-DFA, Zhou [15] introduced multifractal detrended cross-correlation analysis (MF-DCCA) and it has been applied to a number of different markets. For instance, Pal et al. [16] investigated the multifractal cross-correlation behavior on gold, West Texas Intermediate (WTI) and crude oil, and their evidence was supportive of multifractal cross-correlations between crude oil and Indian rupee exchange rate. Li and Lu [17] explored cross-correlations between agricultural commodity futures markets in the US and China. Wang et al. [18] applied MF-DCCA to study the cross-correlations between Chinese A-share and B-share markets. Cao et al. [19] confirmed the existence of multifractality in cross-correlations between RMB exchange rate market and stock market.

Nonetheless, in the MF-DCCA literature, relatively fewer researches have been undertaken to examine the cross-correlation behavior between the crude oil and exchange rate markets. This paper contributes to the existing literature by testing multifractal cross-correlations between the crude oil market and five exchange rate markets, namely Australian Dollars (AUD), Canadian Dollars (CAD), Mexican Pesos (MXN), Russian Rubles (RUB), and South African Rand (ZAR). The 'crossover' analysis is used to study the difference between multifractality in the short term and that in the long term. The present paper also incorporates the rolling windows analysis to further investigate into dynamic features of cross-correlations between the crude oil market and five selected exchange rate markets for oil rich nations.

The rest of this paper is organized as follows. Section 2 explains the MF-DCCA method. Section 3 describes the data for crude oil and the five exchange rates. Section 4 reports qualitative and quantitative results on the cross-correlations between crude oil and five exchange rate markets. Section 5 concludes.

2. MF-DCCA methodology

Suppose that the two time series $x(i)$ and $y(i)$ $(i = 1, 2, \ldots, N)$ are exchange rate returns and crude oil price returns respectively, where N is the length of the series. Then the profile is determined as follows:

$$X_i = \sum_{k=1}^{i} (x_k - \bar{x}),$$
$$Y_i = \sum_{k=1}^{i} (y_k - \bar{y}), \quad i = 1, 2, \ldots, N, \tag{1}$$

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

Next, the two accumulated series $X(i)$ and $Y(i)$ are divided into $N_s = [N/s]$ non-overlapping segments sharing the same length s. Since the length N of the series is not always an integral multiple of the considered time scale s, a small fraction of the profile (1) may remain at the end. To ensure the completeness of the information contained in the time series, the same procedure is repeated starting from the end of the two accumulated series $X(i)$ and $Y(i)$. Through the two procedures, $2N_s$ segments are obtained altogether.

Now, we can calculate the local trends for each of the $2N_s$ segments by an mth-*order* polynomial fit. Thus, the detrended covariance is determined as

$$F^2(s, v) = \frac{1}{s} \sum_{j=1}^{s} |X_{(v-1)s+j}(j) - X_v(j)| \, |Y_{(v-1)s+j}(j) - Y_v(j)| \tag{2}$$