Physica A 434 (2015) 13–24

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Identifying the multiscale impacts of crude oil price shocks on the stock market in China at the sector level

Shupei Huang [a,b], Haizhong An [a,b,c,*], Xiangyun Gao [a,b], Xuan Huang [a,b]

[a] School of Humanities and Economic Management, China University of Geosciences, Beijing, 100083, China
[b] Key Laboratory of Carrying Capacity Assessment for Resource and Environment, Ministry of Land and Resources, Beijing, 100083, China
[c] Lab of Resources and Environmental Management, China University of Geosciences, Beijing, 100083, China

HIGHLIGHTS

- The wavelet transform and Vector auto-regression are incorporated to explore the oil–equity nexus from sector level.
- The impacts of the international crude oil prices shocks are different for sectors in different time horizons.
- The oil price shocks have more impact on Chinese sector stock indices in the medium and long terms.

ARTICLE INFO

Article history:
Received 25 December 2014
Received in revised form 26 February 2015
Available online 18 April 2015

Keywords:
Crude oil price
Stock returns
Wavelet
Vector auto regression model

ABSTRACT

The aim of this research is to investigate the multiscale dynamic linkages between crude oil price and the stock market in China at the sector level. First, the Haar à trous wavelet transform is implemented to extract multiscale information from the original time series. Furthermore, we incorporate the vector autoregression model to estimate the dynamic relationship pairing the Brent oil price and each sector stock index at each scale. There is a strong evidence showing that there are bidirectional Granger causality relationships between most of the sector stock indices and the crude oil price in the short, medium and long terms, except for those in the health, utility and consumption sectors. In fact, the impacts of the crude oil price shocks vary for different sectors over different time horizons. More precisely, the energy, information, material and telecommunication sector stock indices respond to crude oil price shocks negatively in the short run and positively in the medium and long runs, terms whereas the finance sector responds positively over all three time horizons. Moreover, the Brent oil price shocks have a stronger influence on the stock indices of sectors other than the health, optional and utility sectors in the medium and long terms than in the short term. The results obtained suggest implication of this paper as that the investment and policymaking decisions made during different time horizons should be based on the information gathered from each corresponding time scale.

1. Introduction

Time series analysis is a crucial way to identify the hidden information that could yield significant insight into underlying features [1]. Such analysis is complicated by the fact that the time series have nonlinear characteristics [2–5]. Facing the

* Corresponding author at: School of Humanities and Economic Management, China University of Geosciences, Beijing, 100083, China. Tel.: +86 1082 32 3783; fax: +86 1082321783.
E-mail address: ahz369@163.com (H. An).

http://dx.doi.org/10.1016/j.physa.2015.03.059
0378-4371/

nonlinear issue for time series analysis in economic field, the traditional econometrical time series analysis approaches e.g., GARCH (generalized autoregressive conditional heteroskedasticity model), VAR (vector autoregression model), VECM (vector error correction estimates) and the Markov Model are used to explore the relationship between two time series from the holistic aspect. These analyses mainly consider the information from the time domain and ignore the information from the frequency domain, which only offers limited pictures [6–13]. In fact, the hidden time–frequency information of the time series may be the main contributor to the nonlinear features of the time series [14–17].

We take the international crude oil price and domestic stock indices time series for example. The oil–stock nexus could help us to unspool the interaction between the international crude oil markets and national economy [18–20]. More specifically, crude oil price time series contains richer information on a scale-by-scale basis (for different frequency). In other words, the fluctuations of original crude oil price series vary as the scale changes [17]. Simultaneously, the sector stock indices also appear to have multiscale characteristics [16,21–24]. Furthermore, the relationship between the crude oil price and stock indices also behaves in multiscale way [25,26]. Most of the existing literature focus on their correlation and lead–lag relationships that vary as the scale changes [27], whereas few researches are concerned with how the oil price shocks impact on the stock market on a scale-by-scale basis. Hence, the multiscale dynamic interaction between the crude oil price and stock index should be considered using suitable approach, which will offer new evidence on oil–stock nexus.

In terms of multiscale analysis, wavelet transform, particularly the discrete wavelet transform (DWT), offers a perfect solution for circumventing the time–frequency characteristics hidden in the original signals [28–31]. The main objective of the wavelet transform is to use different "resolutions" to observe a signal; in particular, a finer resolution is good at detecting the details of an original signal, and a low resolution is well suitable for the trend analysis. In other words, a time series could be decomposed into different scales, with each scale providing information regarding fluctuations under different "resolutions". The wavelet transform is widely applied in the physics and engineering fields to extract the physical features of the single at first [28,32]. The DWT has recently been applied to explore the multiscale phenomena in the financial time series [33], which offers an effective approach to identifying the multiscale information associated with the oil price and the stock indices [21,25,26,34].

Thus, we aim to explore the multiscale dynamic relationship between crude oil price and sector stock indices. Herein, we consider China for empirical analysis. China has been the second-ranked oil importer since 2009,[1] and the state of its stock market is linked to fluctuations in crude oil price fluctuations [7,35]. In this paper, DWT is first utilized to decompose each original time series of crude oil price and sector stock indices into several sub-sequences, capturing different dynamics in the high frequency domain and the trends in a low-frequency domain. Next, the vector autoregression model (VAR) is adopted to examine the dynamic interaction between crude oil price and the sector stock indices at different scales. Then, the impulse response function is implemented to detect the response direction of stock indices to crude oil price and variance decomposition is used to explain the contribution of crude oil price shocks the sector indices changes at different scales.

2. Data and methodology

The Europe Brent spot oil price is chosen as the proxy for the crude oil price. Because we focus on the Chinese stock market, we examine the China Securities Sector Indices (CSSI), which cover 10 sectors, i.e., Energy, Consumption, Finance, Health, Industry, Information, Material, Optional Consumption, Utility and Telecommunication. The crude oil price is extracted from the US Department of Energy (Energy Information and Administration, EIA) and the CSSI are obtained from the Wind database. The data are all sampled at a daily frequency for period spanning from 2005:1 to 2013:12. The variance of the time series can be effectively reduced by the Haar à trous wavelet transform (HTW) when the time series is stationary [36], which facilitates further analysis. Hence, we convert the data sets to their logarithmic first difference $X_t = \log(s_t/s_{t-1})$.

2.1. Discrete wavelet transform

First, the Haar à trous wavelet transform is used to decompose the Brent and 10 sector stock indices in the joint time–frequency domain to capture different fluctuation features of the original series in at a variety of scales. The HTW applies the successive high-pass and low-pass filters to decompose the original time series; during this process, unlike other discrete wavelet transforms, the HTW abandons the sampling and interpolating processes to effectively retain the information [28,36]. More specifically, S(n) is the input signal, where H(Z) and G(Z) are the transmission functions of the high-pass and the low-pass filter, respectively. A1 and A2 are the approximation coefficients of scales 1 and 2, respectively, and D1 and D2 are the wavelet coefficients of scales 1 and 2, respectively (see Fig. 1).

In detail, the Haar à trous wavelet transform can be represented as an equation involving a series of wavelet coefficients and scale coefficients. First, given the scale coefficient c_{i+1} is defined as follows:

$$c_{i+1}(k) = \sum_{l=-\infty}^{+\infty} h(l)c_i(k + 2^i l). \tag{1}$$

[1] EIA, 2014. Available at http://www.eia.gov/countries/analysisbriefs/China/china.pdf.