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Factor analysis of financial time series using EEMD-ICA based approach

Lu Xian [a], Kaijian He [b], Chao Wang [c], Kin Keung Lai [a,d,*]

[a] International Business School, Shaanxi Normal University, Xi'an 710119, China
[b] School of Business, Hunan University of Science and Technology, Xiangtan 411201,China
[c] Department of Management Sciences, City University of Hong Kong, Hong Kong
[d] Department of Industrial and Manufacturing System Engineering, Hong Kong University, Hong Kong

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ABSTRACT

Analyses of financial time series and exploring its underlying characteristic factors are longstanding research problems. Ensemble empirical mode decomposition (EEMD) and independent component analysis (ICA) are two methods developed to deal with these problems in nonlinear and non-stationary time series. Recently, a new model integrating the two methods (called EEMD-ICA) has been proposed for single-channel signal processing. For better exploration of the underlying factors of single financial time series, this paper attempts to conduct the empirical analysis based on EEMD-ICA model for this task. In the proposed approach, the single financial time series is decomposed into several statistically independent components. The decomposed components reveal more information which include the supply and demand, cycle, economical development and other factors. We find the related economic variable for every decomposed component by analysis and comparison. Finally, the crude oil price is used as the typical financial time series for illustration and verification. The empirical results show that EEMD-ICA based analysis approach is a vital technique for exploring the underlying factors of single financial time series.

1. Introduction

One of the most important goals of financial time series analysis is source extraction and dimensionality reduction. They can help extract features and explore the underlying factors in high-dimensional data with complex features. The understanding of its underlying characterizing features has been the focus of researchers and practitioners in recent years. There have been numerous studies on mining potential factors in financial time series. These approaches mostly can be grouped into two categories: fundamental analysis approaches and econometrics and statistics approaches. Fundamental analysis approaches are mainly based on the causal relationship theory. They investigate the various factors affecting the financial market, analyze the behavioral characteristics of the financial market's variables and explore its inherent law and predict its future change trend [3,8,9,35]. Econometrics and statistics approaches include many linear and nonlinear models, such as Autoregressive Moving Average (ARMA), Autoregressive Conditional Heteroscedasticity type models (ARCH) [10,27,33], Artificial Neural Network [11,26,39], Support Vector Regression [7,12,22], etc.

The financial time series often demonstrate high-frequency, nonlinear, non-stationary and long memory property. Therefore it is difficult to analyze and forecast them by traditional method. In recent years, Ensemble empirical mode decomposition (EEMD) and independent component analysis (ICA) have been developed to deal with nonlinear and non-stationary time series. They have been used extensively and have achieved positive performance improvement in financial time series analysis [1,13,14,18,23,29,34]. For further analysis, a new technique combining EMD and ICA (called EMD-ICA) and the modified EEMD-ICA have been introduced [6,15,16,24].

In this paper, we apply the EEMD-ICA model to single financial time series analysis to identify the underlying factors. In the proposed approach, the original time series is firstly decomposed into statistically independent components (ICs), and then the change trend of each component is investigated. Usually, for each component, we can find a dominant economic factor that caused its oscillation. And these economic factors are very important for the reconstruction of the original time series.

The organization of this paper is given as below: Section 2 introduces EEMD and ICA briefly. Simultaneously, the proposed EEMD-ICA based analysis approach is presented in details. For illustration and verification, the crude oil price is analyzed and modeled in Section 3. Section 4 concludes.

* Corresponding author at: International Business School, Shaanxi Normal University, Xi'an 710119, China.
E-mail addresses: xianlu2010@snnu.edu.cn (L. Xian), kaijian.he@my.cityu.edu.hk (K. He), ccwang6-c@my.cityu.edu.hk (C. Wang), mskklai@cityu.edu.hk (K.K. Lai).

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2. Methodology

2.1. Ensemble empirical mode decomposition

The Empirical mode decomposition(EMD) is a newly proposed adaptive data processing method for nonlinear, non-stationary time series by Huang et al. [30]. Different from other data analysis methods such as wavelet analysis, the decomposition process in EMD is not based on any prior basis function. It decomposes a complex time series into several simpler data components commonly referred to as Intrinsic Mode Functions (IMFs) and the residual series. The IMFs and the residual series are extracted using sifting process [30]. IMFs are extracted one by one, firstly the IMF with the highest frequency, then the IMF with the second highest frequency from the residual of the original data sequence and the extracted IMF. The iterative process is repeated until the condition terminates and the new IMF cannot be extracted. If we denote $c_i(t), i = 1, \dots, N$ to be the resultant set of IMFs and the residual series is $r(t)$, the decomposition of the original time series in EMD method can be expressed as follows:

$$x(t) = \sum_{i=1}^{N} c_i(t) + r(t) \tag{1}$$

Once EMD was proposed, it was widely used and showed great advantages by many researchers [29,38]. But EMD has one inherent drawback, that is the frequent appearance of mode mixing. It is defined as a single IMF consisting of either signals of widely disparate scales, or a signal of a similar scale residing in different IMF components. To solve this problem, Wu and Huang (2008) proposed Ensemble empirical mode decomposition(EEMD). EEMD assumes that the observed data is a combination of the real time series and noise. By adding different noises to the real time series, the population mean value obtained is closer to the real time series. Based on this idea, the main improvement of EEMD is that a pre-processing process is added to the original EMD method. Firstly, the original time series is added to a white noise sequence to obtain a new sequence. Secondly, decompose the new sequence by EMD, and obtain a series of IMFs and residual. Thirdly, repeat the two process, add the new white noise time series to the original time series, and then perform the EMD decomposition. Finally, the decomposed IMFs of the same time scale were averaged, The average of the IMFs was used as the final IMF and the average of the residual was used as the final residual.

EEMD can significantly alleviate the mode mixing problem. The effect of the added white noise on the result can be controlled by the statistical rule, as in (2).

$$\varepsilon_n = \varepsilon / \sqrt{N} \tag{2}$$

Where N is the number of ensemble members, ε is the amplitude of the added noise. ε_n is the error standard deviation. In the literature, the number of ensemble members is often set to 100. The standard deviation is often set to 0.1 or 0.2.

2.2. Independent component analysis

Independent component analysis (ICA) is a new technique to identify hidden factors that underlie sets of observed multivariate data, without any prior knowledge of the mixing mechanisms. It can be seen as an extension of principal component analysis (PCA) and factor analysis. Assume random variable x_i of size $n \times 1$, $i = 1, 2, ..., m$, $m \le n$ generated by a linear mixture of unknown factors denote as s_i of size $n \times 1$, we can obtain [40]

$$X = AS = \sum_{i=1}^{m} a_i {s_i}^T \tag{3}$$

Where $X = [x_1, x_2, ..., x_m]^T$, A is the assumed $m \times m$ static mixing matrix, a_i is the ith column of A and $S = [s_1, s_2, ..., s_m]^T$ of size $m \times n$. The ICA model aims at estimating both A and S using X,with simplified assumptions and constraints. In fact, there are always two assumptions, one is that the unknown components s_i are statistically independent and the other is that there is at most one Gaussian distribution in the independent components (ICs). Several existing algorithms such as Infomax, FastICA, FJADE and CICA can be used for ICA modeling [41]. Among them, the FastICA algorithm is adopted to estimate the de-mixing matrix A and S.

2.3. The EEMD-ICA model

Mijović et al. [6] proposed the EMD-ICA model originally for single-channel signal processing. Recently, this model was improved in the new EEMD-ICA model in two aspects: (1) EEMD replaces the original EMD model to decompose the financial time series for better performance; (2) To reduce the influence of unimportant IMFs, a procedure of recombination is added [24].

The improved EEMD-ICA methodology generally comprises of the following four steps:

1. The financial time series $x(t), t = 1, \dots, T$ is decomposed into N IMFs, $c_i(t), i = 1, \dots, N$ and the residual series $r(t)$.
2. Evaluate the contribution coefficient of the kth IMF (CCI_k) and the residual series by the transformative relative hamming distance (RHD):

$$CCI_k = 1 - \frac{1}{T-1} \sum_{t=1}^{T-1} R(t) \tag{4}$$

   Where $R(t) = 1$ if $(x(t+1) - x(t))(\hat{x}(t+1) - x(t)) \ge 0$, or else $R(t) = 0; \hat{x}(t) = \sum_{i=1, i \ne k}^{N+1} c_i(t)$.
3. Compare all the contribution coefficients with a hard threshold λ, which is a fixed small value (such as 0.2 or 0.3). All the IMFs with smaller contribution coefficients are merged into a new data series. The reserved and merged data series formed a new data set, called VIMFs, $v_j(t), j = 1, \dots, M$ and $M \le N + 1$.
4. Apply the ICA to VIMFs and get statistically independent components $s_k(t), k = 1, \dots, L$ and $L \le M \le N + 1$.

Through linear transformation, we can reconstruct financial time series in terms of the estimated ICs as

$$\hat{x}(t) = \sum_{i=1}^{N} c_i(t) + r(t) = \sum_{j=1}^{M} v_j(t) = \sum_{k=1}^{L} b_k s_k(t) \tag{5}$$

Where b_k is the sum of the kth column of mixing matrix A, and it is called transformation coefficient of the kth IC.

2.4. EEMD-ICA based analysis approach

The EEMD-ICA model provides a new way to explore and model the underlying factors of single financial time series. After we identify the single financial data of interest, the overall process of exploring its underlying factors is described as follows:

2.4.1. Determining the time period of research

The first step is to determine the period of the single financial time series to be analyzed. Especially for the complex financial time series, there are many different driving factors over different time period [21]. Determining the interest period firstly is of great help to explore potential factors more accurately. We can use some special methods to determine the period with certain characteristics, such as structure breakpoint test [4], event study methods [25] etc.

2.4.2. Fundamental analysis

Fundamental analysis method is a based on economic supply and demand theory and the experience analysis. It overcomes the lack of economic meaning problem with the pure data driven analysis method. Therefore, we can preliminarily analyze the possible factors which drive the fluctuations by investigating the structural characteristics of the single financial time series.

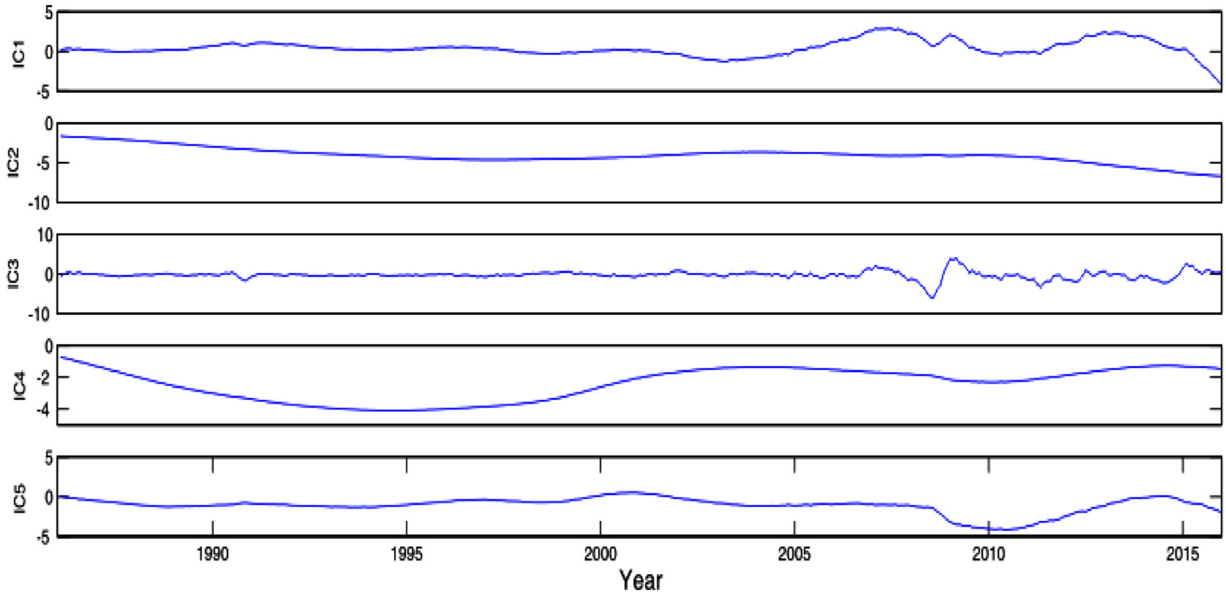

Fig. 1. The ICs for the crude oil price from Jan. 1986 to Dec. 2015 by EEMD–ICA.

Table 1
Descriptive statistics of the estimated ICs.

	b_i	Mean	Skewness	Kurtosis	Correlation coefficient	Hurst exponent	J-B test Statistic
C1	12.72	0.40	−0.20	5.56	0.42(0.00)	0.79	100.6(0.00)
C2	14.26	4.08	−0.01	3.88	0.47(0.00)	0.95	11.7(0.01)
C3	13.53	0.28	−0.91	11.88	0.44(0.00)	0.65	1232.3(0.00)
C4	5.52	2.40	−0.47	1.74	0.51(0.00)	0.99	37.2(0.00)
C5	11.95	1.10	−1.51	5.30	0.39(0.00)	0.98	217.1(0.00)

Note: p-values in parenthesis; b_i is the transformation coefficient of the *i*th IC.

2.4.3. Data decomposition by EEMD-ICA

After the determination of the period and the data analysis, we use EEMD and ICA to decompose the single financial time series of interest into several statistically independent components.

2.4.4. Comparative and economic analysis

We assume that each IC has a concrete meaning in economics. In this step we compare each IC with economic variables referred to in the second step and identify the potential match and correspondence. There are two main ways of comparison, one is trend contrast, and the other is observing the significant change in major point.

In the ICA model, since both S and A are unknown, we cannot determine the variances of the ICs [2], the matrix A is adapted to make the variance of each IC 1. Therefore, our comparison is based on each IC's changing trend rather than its amplitude.

2.4.5. Verification

In this step, we analyze the correlation between economic factors and the extracted independent components to test and verify the derived economic meaning of each independent component.

3. Empirical analysis: exploring the underlying factors of crude oil price

In this section, the crude oil price is analyzed to illustrate and verify the EEMD-ICA based analysis approach. We use the monthly data of West Texas Intermediate (WTI) crude oil spot price which are obtained from the US Energy Information Agency (EIA). They are quoted in US dollars per barrel for our analysis.

3.1. Determining the time period of research

The time period in our research is from January 1986 to December 2015. We select the time period based on following reasons. On one hand, the oil price changes more intensely in recent 30 years. On the other hand, the long time range of this data set provides more information for extraction and modeling. We can also choose other shorter time period, if we are interested in features of a certain time period of crude oil price.

3.2. Fundamental analysis

Different financial time series is always considered with different background and different driving factors. Petroleum has many different attributes, such as resource attribute, commodity attribute, financial attribute, and political attribute, etc. These different attributes make the oil price fluctuations more complicated. The relationships between the crude oil price and the driving factors from different attributes have been investigated in the literature [5,17,19,28,31,34,36,37]. The main factors underlying the oil price include: supply-demand, world economic development, stock market, gold market, US dollar, speculation, geopolitical circumstances, and so on.

3.3. Decomposing data by EEMD-ICA

EEMD-ICA is applied to decompose WTI crude oil spot price, with a total of 360 data points. The number of ensemble members is set to 100, the standard deviation of white noise series is set to 0.2, and the hard threshold is set to 0.3 in our analysis. The crude oil price is decomposed into 5 ICs. Fig. 1 shows the visualization.

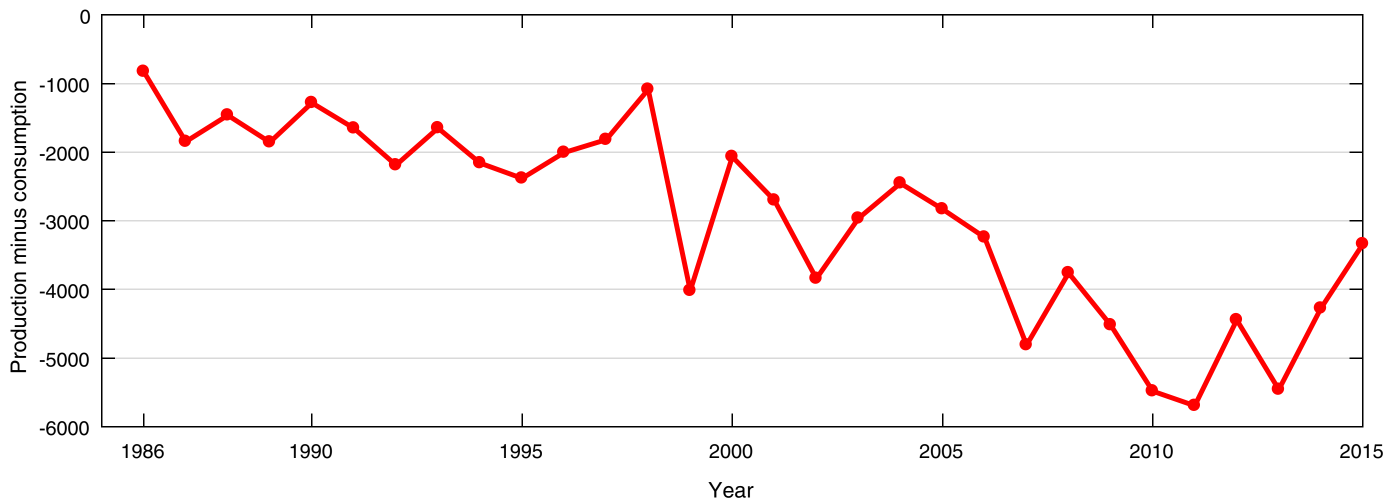

Fig. 2. The crude oil production minus consumption from 1986 to 2015.

Table 2
Robust regression of the estimated ICs on the relevant economic variables.

	Intercept	Coefficients	R^2	Adjusted R^2	F-stat
IC1 on US dollar	3.77***	0.11***/−0.04***	0.29	0.29	72.5***
IC2 on Supply & Demand	2.21	3.8e-04**/3.25e-04*/2.38e-03*	0.53	0.48	9.43***
IC3on Geopolitics & Speculation	−0.98**	4.60e-05**/−3.25e-08***	0.34	0.29	6.77***
IC4 on Cycle	−2.72***	0.52**/−0.46**	0.2	0.14	3.24*
IC5 on Finance	−0.76***	3.1e-04***/1.16e-03***	0.45	0.45	145***

Note: US dollar includes the consumer price index (CPI) in US and US dollar index; Supply and Demand includes crude oil production, consumption and proved reserves in world; Geopolitics & Speculation includes the world's annual oil trade and GDP; Cycle includes the world's GDP growth rate and US GDP growth rate (annual%); Finance includes the Nasdaq Composite Index and the gold price. * p<0.1,** p<0.05,***p<0.01.

3.4. Compare and economic analysis

The mixing matrix A and its inverse are also obtained during the decomposition process. From Eq. (5), the reconstruction of crude oil price can be shown as

$$\hat{x}(t) = \sum_{k=1}^{L} b_k s_k(t) = 12.72s_1 - 14.26s_2 - 13.53s_3 + 15.52s_4 - 11.95s_5 \qquad (6)$$

The next step is to explore the economic meaning of each IC by careful comparison and analysis. Analyses of the statistical characteristics of ICs can help to gain better insights. Table 1 shows related statistical information about the ICs, including mean, skewness, kurtosis and Hurst exponent, correlation between each IC and the crude oil price, Jarque–Bera(J–B) test for normality, and so on. The transformation coefficients of the ICs are also listed.

From Table 1, we find some important information. First, all ICs are distinctly non-Gaussian, as the J-B test are all significant at the 5% confidence level and the ICs' kurtosis are far from 3. Second, the correlation coefficients between ICs and crude oil price are similar. This result shows that ICs' corresponding economic variables are of almost equal importance for crude oil price fluctuations. Third, all the Hurst exponents are greater than 0.5, it means all ICs have long-term memory.

US dollar is the major invoicing currency in the international crude oil markets, and the US dollar exchange rate always play counteracting effect on crude oil price fluctuation [32,34]. Through the observation of IC1's fluctuation in some periods (such as 1993 to 2002, 2003 to 2007, 2014 to present), we can find that the change trend of IC1 is always contrary to the US dollar index. Hence, IC1 can be seen as the factor of US dollar.

The second IC changes slowly, and remains at a certain high absolute value; it represents the change of oil supply and demand situation, as both IC2 and the value of oil production minus consumption have the same descending trend, as shown in Fig. 2. There are many factors which affect the oil supply and demand, including oil reserves, production, consumption, the development of alternative energy sources and so on.

Crude oil is always a critical strategic policy tool of international politics and IC3 reflects these political and other extreme events effects perfectly. It has the highest fluctuation frequency among all the ICs. Events such as the Gulf War in 1991 and the global financial crisis in 2008 represent the corresponding changes in IC3. The behavior of speculative funds exacerbated these impacts.

IC4 reveals the cycle fluctuations of crude oil prices. As important energy resource and commodities, crude oil usually shows close relationship with economic growth [20]. This suggests that global and some regional economic development cycles and seasonal consumption impetus are main cause of the oil's fluctuant cycle.

For the financial attribute, there usually exists a very strong relationship between the stock market, gold market and crude oil market. IC5 seems to be consistent with these influences, especially at some important time points, such as around 2000 and 2008 to 2009.

3.5. Verification

From the above analysis, some main underlying factors of the crude oil price have been found. Next we will test and confirm our analysis by regression analysis. Regression analysis is carried out with the following three considerations. Firstly, in our analysis, we use the robust regression instead of the simple ordinary least-squares (OLS) for its sensitivity. Secondly, these economic variables are not always quantifiable, such as economic cycle, geopolitics and speculation. Thus we use some proxy variables, and the specific contents are shown in Table 2. Thirdly, since data for some economic variables such as GDP, oil production and consumption, etc. are only available at yearly frequency, data for their corresponding ICs are converted to the annual frequency.

The regression results are reported in Table 2, and provide the statistical evidence about the linear relationship between ICs and related economic variables.

4. Conclusions

In this paper, we apply the EEMD-ICA based analysis approach to explore the underlying factors of single financial time series using the crude oil price as an illustration and verification example. The significance of our research work can be summarized as follows.

(1) A complete single financial time series analysis approach has been applied. And this method can be easily extended to other fields, such as signal processing, forecast, and feature extraction.
(2) The decomposition method separates the complex financial time series into several simple independent parts. This helps to analyze the underlying information on various scales accurately.
(3) Our approach provides the alternative approach to analzye financial time series, which is different from previous approach to set one model and several fixed variables, and then estimate the effects of each variable. Our appaorch gets the effects of each IC by automatically decomposing and exploring each IC's corresponding economic meaning.
(4) As one of the most important commodities in the world, we analyze the crude oil price for illustration and verification. The empirical results show that our EEMD-ICA based analysis approach is vital and effective.

Declaration of Competing Interest

We declare that we have **no** financial and personal relationships with other people or organizations that can inappropriately influence our work, there is **no** professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

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