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Price fluctuation in the energy stock market based on fluctuation and co-fluctuation matrix transmission networks

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ABSTRACT

Few studies address fluctuation and co-fluctuation patterns in the short term or their roles and transmission pathways over the long term. Here, we used the 10-year daily price of the NASDAQ Top 10 listed energy companies to obtain daily returns of each energy stock. The daily fluctuation and co-fluctuation patterns, roles and relationships were studied based on the fluctuation transmission network (FTN) and co-fluctuation matrix transmission network (CMTN). We found that each energy stock has a different price fluctuation feature, and any two of them have obvious positive correlations; however, only four-ninths of them have spillover relations. For the FTN, we transformed each daily return into a symbol and combined the symbols into a fluctuation pattern; next, the fluctuation pattern was taken as a node and the pattern adjacent relations as edges to construct the network. For the CMTN, we transferred the daily return relations for any two energy stocks to the daily co-fluctuation matrices and then constructed the network based on the time adjacent relations. Then, we used and also defined some coefficients to analyze the roles of each fluctuation and co-fluctuation pattern and their relationships. This paper provides a novel method for researching fluctuations in energy financial market.

1. Introduction

Energy is one of the key components of economic and social development [1]. In addition to the development of energy financial markets, the financial aspect of energy has become more and more significant. Energy stocks are an important part of energy finance [2] and a popular component of portfolios dedicated to energy investment. Investors understand that energy stocks with higher returns and less fluctuation are a better portfolio choice. In addition, portfolio stocks should not have obvious cross-correlations. Previous studies have proven that the price and return of energy stocks are influenced by many factors [3–5]. However, energy investors need to know the fluctuation and co-fluctuation features of energy stocks.

Usually, the correlations and interactions between times series in a certain time either short or long has been well studied by some certain values calculated by different methods, such as the Pearson Correlation Coefficient, GARCH model [6], and other multifractal analysis models, such as MF-DFA, MF-SSA, and MF-DCCA models [7–10]. However, there are hundreds of different time series in financial market, which have different fluctuation and co-fluctuation patterns at the same time, and in order to study the inner-relations of these time series, besides the certain values of a certain period, to find out how the multi financial time series interact with each other in the unit time and what is the transmission relations between the interactive patterns are very important and still left to be answered. In energy markets, for portfolio choice and risk analysis, many studies research fluctuation and stability features by analyzing the statistical features of a single time series, such as the mean, the standard deviation of the stock price, stock returns, futures and options prices and the stock index [11], as well as the correlations and cross-correlation between two

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groups of time series, such as stock returns and firm size [12], stock returns and future returns [13], energy futures contracts and energy indexes [14], different stock indices [15], and the energy spot price of different spot markets [16,17]. Most of these studies focus on the correlation or spillover relations over a long period with a certain value. However, energy stocks and other financial time series exhibit uninterrupted fluctuation each trading day or even each second. If the energy investor only takes long-term relations into account for portfolio decisions, important information about the short term is missed. It is necessary to study the fluctuation and co-fluctuation patterns and roles of multiple energy stocks in the short term and their transmission features and transmission ability from a holistic perspective.

Complex networks are often used to find the role of nodes as well as the relations between them from a holistic point of view. This is a new but popular method to simulate the interactive relationships in both the energy financial market [2,18,19] and the energy commodity market [20–22]. Previously, complex networks were widely used to analyze networks constructed from section data and its evolutionary features [2,23,24] as well as bivariate time series [25,26]. However, few studies have addressed the interactive relationships of multiple time series based on complex networks. As the concept of the "network of networks" [27,28] is becoming increasingly popular, more and more scholars have begun studying not only single nodes with simple attributes but also the interactive relationships of each node. Typically, there are also many sub-individuals, and these sub-individuals have their own as well as interactive relations with each other; these relations can also form a group pattern, a sub-network or an interactive matrix [29]. Researching both the whole network and these sub-individuals can help us analyze both the roles and relationships of the individual from a holistic perspective and the interactive relations of sub-individuals in detail.

The forgoing studies reveal the fluctuation and co-fluctuation patterns of multiple energy stocks in the short term, as well as their roles and transmission relations in the long term. We chose the Top 10 energy stocks based on their market capital in the NASDAQ stock market as an empirical sample, and then, based on the idea of "coarse gaining" [26,30], both the price fluctuation patterns and co-fluctuation matrices of the 10 energy stocks were obtained; next, based on the adjacent relations of the trading days, we constructed both the price fluctuation transmission network and the co-fluctuation matrix transmission network. To analyze the roles of fluctuation patterns and the co-fluctuation relationships, we used and defined different coefficients and also performed a comparative analysis using the statistical features of returns. This is a novel method for understanding the features and correlations of the energy stock market based on fluctuation and co-fluctuation patterns in the short term and from a holistic perspective.

2. Data and methods

2.1. Data

To study the fluctuation and co-fluctuation patterns of multiple energy stocks, it is first necessary to choose some representative energy stocks. Because different stock markets have different trading days, we choose well-known energy stocks that are listed on the same international stock market, i.e., the NASDAQ (http://www.nasdaq.com/). The original data were mainly extracted on May 12th, 2015. There were 360 energy companies listed on the NASDAQ stock market on that day, and we chose only the top ten listed energy companies, whose combined market capital comprises more than 50% of the total market capital of the energy sector on the NASDAQ stock market. The downloaded documents include information on the Top 10 listed energy companies; Table 1 shows information on the ten listed energy companies and the ten-year daily stock close price record for the Top 10 listed energy companies from May 09, 2005, to May 08, 2015 (2518 trading days). Fig. 1 shows the stock price of the Top 10 listed energy companies for the last ten years; these energy companies are from different countries and belong to different "subsectors"; however, energy investors view them as the most attractive energy investment targets because of their capital strength, and they are the leaders of the energy stock market, influencing not only domestic energy markets but also the global energy market.

2.2. Methods

2.2.1. The return rate and correlation coefficient of energy stocks

To discover the price fluctuation of each energy stock, we define the return rate as the percentage change in the close price compared to the previous day (see Formula (1)).

$$r_{i,t} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}} \tag{1}$$

where $r_{i,t}$ is the return rate of stock i, $p_{i,t}$ is the close price of stock i at trading day t, and $p_{i,t-1}$ is the close price of stock i at trading day t-1. Here, to obtain the return rate of stock i at $t = 1$, we also need to know the close price of f stock i at $t = 0$; we therefore assume that May 09, 2005 is trading day 0 ($t = 0$) and May 08, 2015 is trading day 2517 ($t = 2517$).

Meanwhile, to analyze the statistical features of the multiple energy stock returns and their relationships, we used the Pearson Coefficient to show the correlation between energy stocks and to analyze the inner relations between energy stocks. We also used an econometrics model, the generalized autoregressive conditional heteroscedasticity model (the GARCH model) [6], to determine the

Table 1
Information regarding the Top 10 listed energy companies in terms of market capital.

Symbol	Name	Country	Subsector	Market capital (Dollars)
XOM	Exxon Mobil Corporation	United States	Integrated oil Companies	3.62837×10^{11}
GE	General Electric Company	United States	Consumer Electronics/Appliances	2.71244×10^{11}
PTR	PetroChina Company Limited	China	Oil & Gas Production	2.23524×10^{11}
CVX	Chevron Corporation	United States	Integrated oil Companies	2.01888×10^{11}
BP	BP p.l.c.	United Kingdom	Integrated oil Companies	1.41976×10^{11}
BBL	BHP Billiton plc	United Kingdom	Coal Mining	1.30086×10^{11}
TOT	TotalFinaElf, S.A.	France	Oil & Gas Production	1.20143×10^{11}
SLB	Schlumberger N.V.	France	Oilfield Services/Equipment	1.16523×10^{11}
SNP	China Petroleum & Chemical Corporation	China	Integrated oil Companies	1.07008×10^{11}
COP	ConocoPhillips	United States	Integrated oil Companies	80486755092

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