

Stock Investment Strategies with Time-Varying Co-Movements Between Energy Market and Global Financial Market

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Abstract. One of central challenges in guiding investment management is how to intelligently identify investment strategies. This paper sets up a deeping learning model for realizing stock investment strategies with time-varying co-movements between energy market and global financial market: It uses LSTM neural network approach to predict energy stock price, and employs the improved time domain connectedness measures of Diebold and Yilmaz to test the spillover mechanism of market volatility shocks. By the proposed model, this paper explores the time pattern of volatility spillover between energy market and stock price in major global financial markets (mainly including stock market) from January 3, 2000 to December 31, 2020.

Keywords: Component, formatting, style, styling, insert.

1. Introduction

Energy is a critical input in modern economic systems. It is critical to further study the energy market issues from the perspective of economic globalization [1]. Traditional financial theory suggests that the fluctuations in oil prices may have an impact on stock market returns. The change of oil price has symmetrical influence on the stock market. Some scholars suggest that oil assets should become an indispensable part of diversified stock portfolios. Investors can hedge stock investment risks by short positions in the oil futures market at a lower hedging cost [2]. In addition to the energy market represented by oil, the energy market represented by carbon resources and natural gas will also have an impact on the global financial market [3]. The spillover relationship between energy market and global financial market is worth studying, and the stock investment strategy is proposed based on this spillover relationship.

From the perspective of investment application, market participants should pay more attention to the size and direction of net income spillover contribution of different asset classes in their portfolios. Diebold and Yilmaz introduced a simple measure of connectedness that explicitly takes into account the interdependence of financial markets. This paper uses this method to calculate the spillover effect between markets [4]. Stock price is a common time series data, which is usually processed by long-term and short-term neural networks (LSTM). As a further extension algorithm of recurrent neural network, the main advantage of LSTM is that it overcomes the requirement of learning long-term time dependence. The innovation of Deep learning is that it automatically identifies patterns in spatiotemporal data with higher accuracy than human beings. The application of deep learning in the field of economics is also increasing.

At present, there are mainly the above two stock prediction and analysis methods in the stock market, one is the fundamental analysis method, the other is the stock technical analysis method. They both have certain drawbacks. The stock price trend forecast is a huge system, which is affected by many factors. Zhang and Wu (2009) pointed out that stock prices are often affected by other factors, such as changes in the political environment and the development of relevant stock markets [5]. However, by constructing a quantitative model, on the one hand, a large amount of data can be quickly calculated to mine hidden useful information; on the other hand, the subjective judgment of investors can be minimized to be as objective as possible. Neural network is one of the common stock prediction models. This paper combines spillover index method and neural network to analyze the relationship between global financial market and energy market from two aspects of spillover relationship and stock price volatility.

The structure of the article is as follows. The first section proposes research questions. The second section mainly describes the research methods of the paper. The third section is the results, and discussion and the last section is the conclusion.

2. Method

Following Refs. [6], we set up a Deeping learning model for realizing stock investment strategies: It uses LSTM neural network approach to predict energy stock price and employs the improved time domain connectedness measures to test the spillover mechanism of market volatility shocks. The spillover index method is widely used to test the directional correlation of variables, and Deep LSTM is used to predict energy stock prices. The model structure is as Figure 1. One of the research methods of this paper is based on the improvement of DY overflow index method. Concurrently, the performance of LSTM for time series problems is not satisfactory. We use Deep LSTM(DLSTM) here to deal with the prediction of energy stock price.

Model input. The inputs of the model include global financial market data and energy market data. The stock market, enterprise financial reports and financial indexes can be used as data sources. How to reasonably represent the global financial market and energy market through data is not only the difficulty and focus of model input, but also the basis of the model. Method introduction and steps. This method is based on vector autoregressive (VAR) model and can be used to measure the degree of interaction between variables. We need to establish VAR model and define various spillover indicators. Spillover indexes are divided into static spillover index and dynamic spillover index. The Deep model is a corresponding extension of the original LSTM model, which trains the prediction model more effectively. This paper applies DLSTM to predict the energy stock price. **Model output.** The output of the model is divided into the prediction of spillover relationship and energy stock price. Spillover relationships include total spillover index, directional spillover, net volatility spillover and net paired volatility spillover.

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3. Results and discussion

By the propsed model, this paper explores the time pattern of volatility spillover between energy market and stock price in major global financial markets from January 3, 2000, to December 31, 2020.

3.1. Spillover index method

For the research on the spillover effect of energy market and global financial market, one of the research methods used in this paper is the spillover index method proposed by Diebold and Yilmaz. In this paper, the lag order of the VAR model of each sequence is set to order 4, and the prediction error step h is set to 10 days with reference to Diebold and Yilmaz. **Model input.** Energy mainly includes oil, coal, natural gas, etc. Crude oil is by far the most popular application in energy economics/finance. This paper selects oil as a typical representative of energy market for empirical analysis. The daily closing price of Duke Energy (DUK) is used to represent changes in oil energy. Included are the following variables from financial markets: (I) DOW and S&P500. (II) FTSE 100 (proxies for U.K. stock market). (III) ShenZhen Securities Component Index (SZI) (proxies for China stock market). We select daily closing price from January 3, 2000 to December 31, 2020.

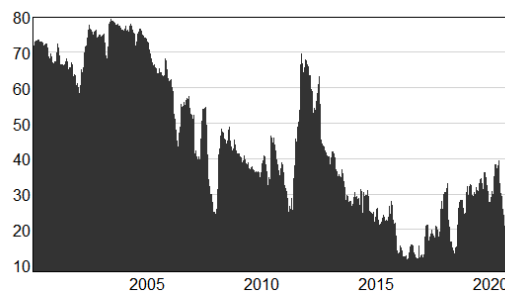


Fig. 1 The total spillover index

Dynamic spillover index. (I) The total spillover index, as Figure 2. Observing the total spillover index of the energy market and the global financial market under the rolling sample, we can find that the total spillover index between markets increases and decreases in different ranges with time. From 2000 to 2005, the total spillover index was at its peak, and the spillover effect was obvious. The total spillover index fluctuated and decreased in subsequent years and fell to the lowest range from 2015 to 2017. (II) The directional spillovers, as Figure 2. TO spillover index indicates the spillover effect of single market on other markets, and FROM spillover index indicates the spillover effect of other markets on single market. The directional spillovers between markets show volatility changes. In the time sample, DUK has been at the peak of receiving spillovers from other markets, but the spillover output to other markets gradually decreased from 2010 to 2020.

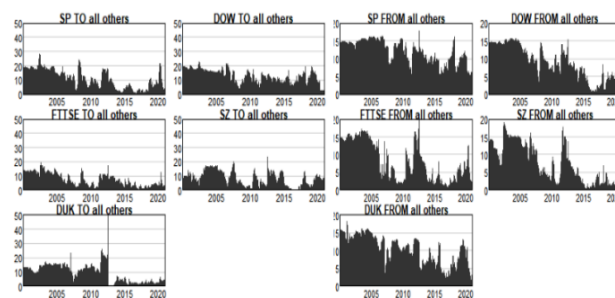


Fig. 2 The directional spillovers

(III) The net volatility spillovers, as Figure 3. The total directional giving index minus the total directional receiving index constitutes the net volatility spillovers index, which represents the net spillover effect of a single market on other markets. In the time sample, DUK is mostly the net importer of spillover, and has continuously become the net importer of spillover from 2013 to 2020, and DOW is mostly the net exporter of spillover. The result of net volatility spillover shows that the energy market receives the spillover effect of global financial markets.

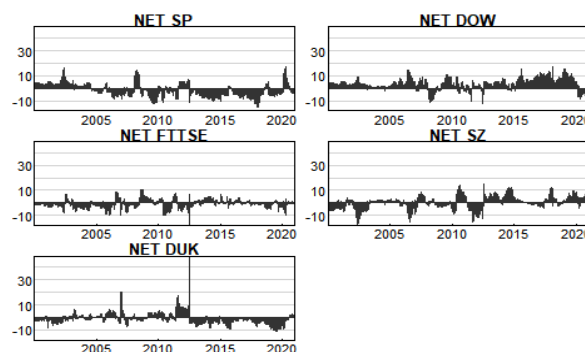


Fig. 3 The net volatility spillovers

(IV) The net pairwise volatility spillovers, as Figure 4. If more than two markets are analyzed, the net pairwise volatility spillovers index can be used to measure the volatility spillover effect between the two markets. DUK has been the net importer of the fluctuation spillover effect for most of the time. Especially from 2013 to 2020, DUK has continuously become the net importer of the fluctuation

spillover effect of DOW S&P500, FTSE 100 and SZI. The global financial markets affect each other, and there are periodic spillover effects, net importer and net exporter.

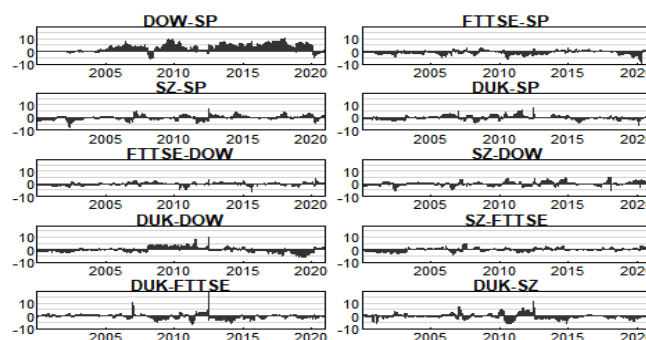


Fig. 4 The net pairwise volatility spillovers

3.2. Empirical analysis of energy price forecast

This paper uses the stock changes of international well-known oil energy enterprises to simulate the changes of oil energy, and forecasts the oil stock price. Enter the selection of features. We select the technical indicators of the opening price of these stock indexes for data prediction and analysis. All data were standardized by Z-score. The output of this model is the predicted value of the opening price of Duke Energy stock the next day.

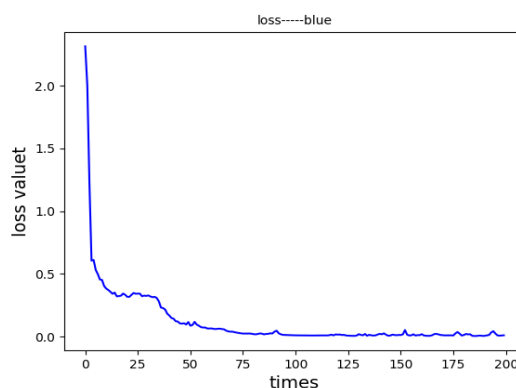


Fig. 5 Loss function of training data

Determine parameters through genetic algorithm. When learning rate=0.0006, number of hidden layers=3, Number of neurons (single layer) =3, Number of iterations=200, The model performs well on the training data. When the number of iterations reaches about 100, the loss function value is lower than 0.5 and tends to be stable. In addition, when model parameters are used to test data, the performance is still impressive. The loss function value of the model has always been lower than 0.5. The model prediction result on the test data is relatively close to the real stock price, as shown in the figure below. The model's fitting ability and generalization ability are strong.

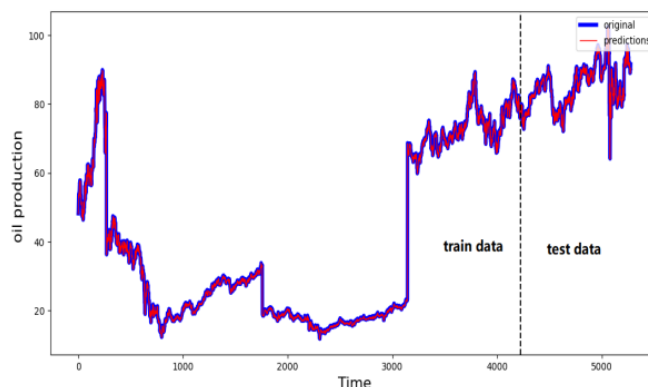


Fig. 6 Predicted results of test data

4. Conclusion

We explore the dynamic relationship between global financial market and energy market by using some internationally renowned indexes and the stock change data of DUK company. The main findings of the study conclude that oil shocks are exogenous and contribution of oil market volatility in global financial markets is insignificant. We find that the energy market, as the net importer of the spillover effect of the global financial market in the past 10 years, is more affected by the global financial market. The investment strategy for top-down investors focuses on the allocation and development of countries and industries. When investing in the energy market, such as oil energy, investors need to comprehensively consider the spillover effect of the financial market on the energy market.

There are still some shortcomings in this article. In further research, we can consider the increase in sample size, increase in stock financial data, and more professional investment strategies.

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