The Influence of COVID-19 Epidemic on the Financial Market of China Energy Industry

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Abstract. Aim to reveal the changes in the financial market of the energy industry in China under the influence of the COVID-19 epidemic by use the fluctuation of the stock price of the energy industry. In this paper, ARIMA, a time series autoregressive moving average model, is used to model the fluctuation of stock prices in the energy industry, it shows the impacst on the financial market of energy industry before and after the outbreak of epidemic, in order to understand the energy crisis under the COVID-19 epidemic more clearly through this study. This research found that based on the COVID-19 pandemic, the stock price of the energy industry fluctuated. The epidemic caused investors' lack of confidence in the market, which caused the stock price to fall. Later, due to the government's policy to save the market, the stock price rebounded. Different from other research based on global nature, this paper focuses on energy enterprises in China. This study is meaningful. For investors, by understanding the changes in the financial market, they can regain confidence in the market. For leaders, this study can let them know the serious impact of epidemic on the market, respond to the rescue more quickly, and introduce the rescue policy.

Keywords: COVID-19, Financial market, Stock price, China energy industry.

1. Introduction

In 2020, once the COVID-19 epidemic broke out, it quickly spread to the whole world. At the same time, it is also recognized by the world as the fastest transmission speed and the greatest prevention difficulty [1]. It has brought great impact on the consumption of global residents and the production activities of enterprises. The financial market has always been regarded as the most intuitive place to discover economic changes, and emergencies such as the new crown epidemic will be reflected in the stock markets of related industries in the first time. According to the research of Zhang, Hu and Ji, once the epidemic broke out, the economic situation in the United States turned sharply [2]. The stock market in the United States was once close to collapse, and its fuse occurred four times, with an interval of no more than ten days. A similar thing happened in the UK, and the data showed that the FTSE index in the UK fell the most in the past 30 years [2].

It can be found in many previous literatures that due to the speed of COVID-19 epidemic and the difficulty of prevention, governments all over the world have taken corresponding epidemic prevention measures. For example, restrict certain vehicle trips and store operations [3]. However, this restriction has undoubtedly brought negative effects on energy demand in various countries. The research of Shaikh shows that the global crude oil price has also fluctuated greatly, falling by more than 50% in the first quarter of 2020 alone [4]. This negative impact directly caused the financial market of the energy industry to fluctuate. For example, during the outbreak of COVID-19, the oil price crisis may lead to the possibility of high risk of oil assets [5]. Similarly, Mzoughi, Ghabri and Guesmi also find the COVID-19 epidemic may affect the entire energy industry market, including oil prices [6].

Compared with Europe, America and other countries, China is even more affected. Because China has adopted a stricter epidemic prevention policy, for example a series of isolation measures such as "closing the city", it has undoubtedly deepened its influence on the financial market of the energy industry. The restriction of personnel mobility and some blocked economic activities caused by "city closure" will lead to the decline of energy demand [7]. In Aydın and Ari's research, the epidemic situation has brought a serious impact on the stock market of energy enterprises [8]. In the context of the worsening epidemic situation in COVID-19, investors' expectations for the future of the energy industry are biased in a bad direction, and even think that the corresponding investment strategy should be changed [9]. From the above discussion, the energy industry was almost one of the industries that suffered the most during the epidemic.

Scholars have done a lot of research on the impact of epidemic on the global financial market, and achieved many very meaningful research results. However, most of the past literature research is based on global economic activities, and few studies focus on energy industry and China enterprises. Therefore, this study will take China's energy industry as the research object, and use time series and autoregressive moving average model ARIMA to make up for this gap to some extent. It can help people who want to know about the changes in the energy industry and policy makers in the energy industry to understand the energy crisis under the COVID-19 epidemic more clearly, thus enriching the literature and making contributions.

This paper *has the following structure*. The secondly part will introduce the research design of this study, the thirdly part is the empirical results and analysis, the next part is the critical discussion, and conclusion is the final part.

2. Research and Design

2.1. Data source

To investigate the impact of COVID-19 on energy industry in China and the current situation of China's energy industry, this study chooses the stock prices of large energy enterprises listed on the Shanghai Stock Exchange as the research object. Arouri, Jouini and Nguyen show in their research that the change of energy demand can affect the cash activities of enterprises and the stock price [10]. The data comes from the statistical data of investing database. In order to compare the difference of stock prices before and after the epidemic, the data time span of this study is from 2016 to 2020, which is the daily data, weekly data, and monthly data of the four years before the epidemic and the year of the epidemic, so that this study can observe the data volatility more clearly.

2.2. Weak Stationarity Test

This study adopts the method of time series prediction and analysis, so it is significance to test the unit root of time series to determine its stability before the model study. If it is an unstable sequence, it needs to be differentiated so that the sequence can be transformed into a stable sequence. Caner and Kilian described in their research summary that in order to present the stability of data, when determining whether the data should be differentiated by time function first, the unit root test can be applied here at this time [11]. In this study, the original hypothesis of the test is that the sequence is unstable, and the data are shown in Table 1.

Table 1. Weak stationarity test

	t	p
Daily		
Raw	-2.125	0.5320
1st order difference	-23.095	0.0000
Weekly		
Raw	-2.171	0.5061
1st order difference	-9.791	0.0000
2nd order difference	-16.260	0.0000
Monthly		
Raw	-2.347	0.4082
1st order difference	-5.957	0.0000
2nd order difference	-6.758	0.0000

According to Table 1, it can be clearly seen that the P value of logarithmic price series of daily, weekly and monthly data is greater than 5%, and the original hypothesis is accepted, and the series is unstable. Therefore, in this study, the daily data, weekly data and monthly data are all differentiated, and the P value after differentiation is 0, which indicates that stable time series data has been obtained, so the differentiated data is selected to establish the model.

2.3. ARIMA Model Setting

Analyze and predict the data by use ARIMA model. ARIMA model can be used to explain many models, such as constant or changing volatility [12]. Autoregressive -AR, difference-I and moving average -MA can form ARIMA model. In ARIMA (p, d, q) model, the autoregressive term is denoted as p, moving average term is denoted as q, differences are denoted as d. The ARIMA model can be divided into three parts, as shown below.

2.3.1. AR Model

AR model is an autoregressive model, which needs to meet the requirements of stationarity. The historical value data of the variable is used to predict the relationship between the historical value and the current value. In this study, AR model uses the past stock prices of China energy industry from January 2016 to August 2020 to estimate the future value. As shown below:

$$y_t = \mu + \sum_{i=1}^{p} r_i y_{t-i} + \varepsilon_t \tag{1}$$

The formula can be transformed into:

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \cdots + \alpha_p x_{t-p} + \mu_t \tag{2}$$

$y_t$is the present worth, μ is a constant term, p is the order, r_i is the coefficient of autocorrelation, ε_t is the error. If the autocorrelation coefficient is less than 0.5, it should not be used [13]. The formula can be transformed into as follows, if the term randomly disturbed is white noise:

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \cdots + \alpha_p x_{t-p} + \varepsilon_t \tag{3}$$

2.3.2. MA model

MA model can remove random fluctuations in forecasting [13]. When the historical value of time series is only related to historical white noise, the MA model uses the error term to predict, as shown below:

$$x_t = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q} \tag{4}$$

2.3.3. ARIMA Model

Combining (3) with (4), we can get ARMA model. As shown below:

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \cdots + \alpha_p x_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q} \tag{5}$$

Because this study needs to ensure the stability of data, the time series data are differentiated, so the difference is added to ARMA model, and the model ARIMA is obtained.

3. Empirical Results and Analysis

3.1. Order Determination

In this chapter, the first thing to do in this study is to ascertain p, q and d's value of China energy industry stock price in ARIMA model in three kinds of time (day, week and month), to facilitate the next research and prediction of this study and apply PACF and ACF charts here. The correlation between past and present observations of time series can be described by autocorrelation function [11]. When the intermediate observation value is given, the partial autocorrelation function is used instead of autocorrelation to describe the linear correlation between the past and present observation values of time series [12]. At the same time, it should be noted in PACF and ACF diagrams that the regions bounded by y=-0.1 and y=0.1 refer to the 95% confidence intervals of AR(p) and MA(q).

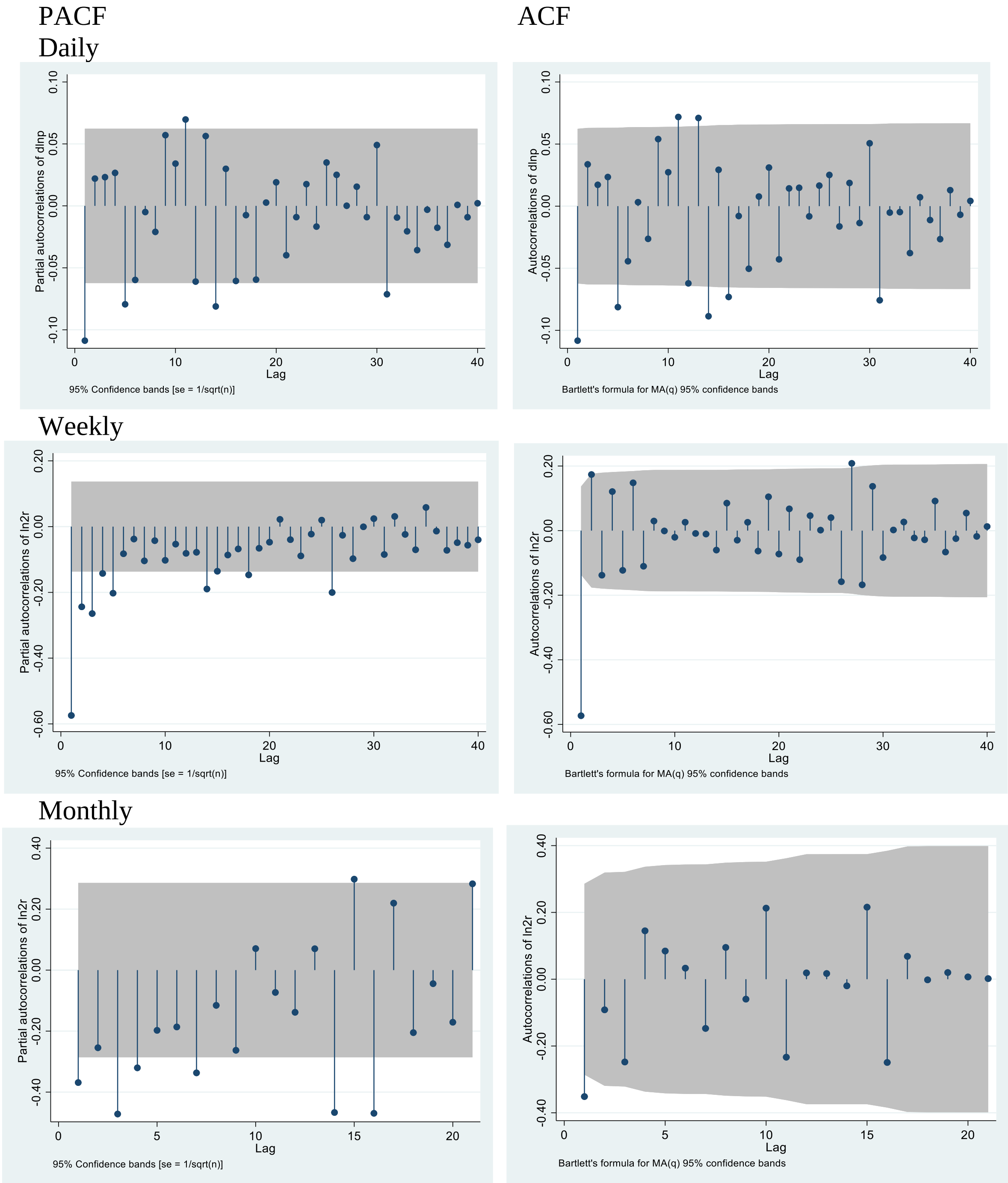

Figure 1. ARMA (p, q) identification
Photo credit: Original

According to Figure 1, it can be clearly seen that in the daily data, the p of ARIMA model is 5 and the q is 5, which is divided into d by the first-order difference made in 2.2 above, so the daily data is ARIMA (5,1,5). In the weekly data, the p of ARIMA model is 5, and the q is 1. Because the first-order difference cannot determine the order, d is 2, so the weekly data is ARIMA (5,2,1). In the monthly data, the p of ARIMA model is 7 and the q is 1. Similarly, because the order cannot be determined by the first-order difference in the monthly data, therefore d is 2, and the monthly data is ARIMA (7,2,1). After the order of the model is determined, this study also needs to test the residual of the model. The results of testing the model residuals in this study are shown in the following figure.

Table 2. Residual test

Model	Portmanteau (Q) statistic	Prob > chi2
Daily-ARIMA (5, 1, 5)	52.2791	0.0924
Weekly-ARIMA (5, 2, 1)	48.3298	0.1718
Monthly-ARIMA (7, 2, 1)	164.7369	0.0000

The residual test's original hypothesis is that the tested data does not have any autocorrelation, which means it is white noise. It can be clearly seen from Table 2 that the p values of daily data and weekly data are both greater than 0.05, which accepts the original hypothesis and has no autocorrelation. However, the p value of monthly data is 0, which rejects the original hypothesis and the model representing monthly data is not sufficient. Because the predicted value in this study is not very accurate, the monthly data can be used as a reference.

3.2. Forecast Results and Interpretation

This study uses the above model and STATA statistical data analysis tool to analyze the data and get the following results, as shown in the following figure, which are the actual values and fitting values of daily, weekly and monthly data respectively.

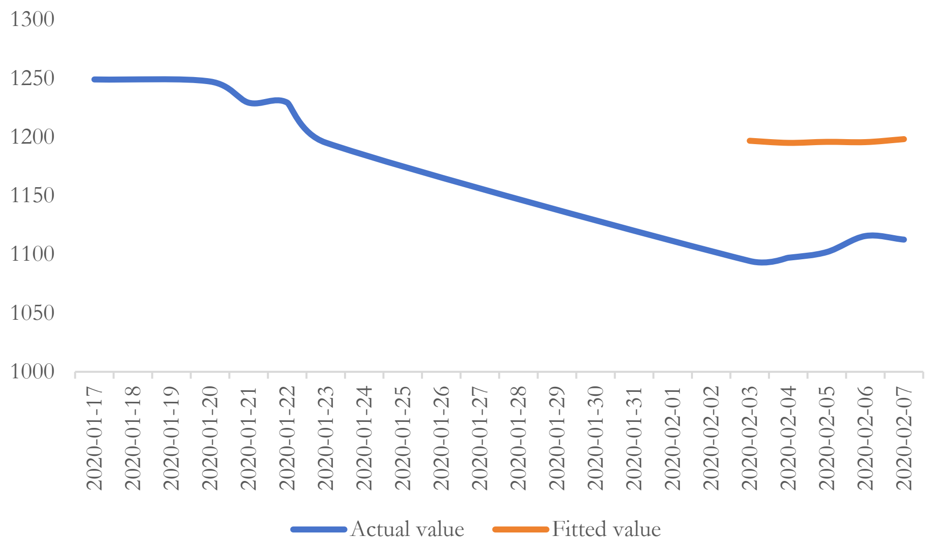

Figure 2. Daily
Photo credit: Original

According to Figure 2, it can be clearly seen that the first is the daily data. Before the outbreak of the epidemic in January 2020, the stock price of the energy industry was at a relatively stable value, and the stock price dropped slightly near the New Year, which may be due to some investors selling their stocks and withdrawing funds to go home for the New Year, which is a relatively normal phenomenon. However, after the outbreak of COVID-19 epidemic in January, we can see that there was a considerable gap between the actual value and the fitting value of the stock price just after the Spring Festival. On February 3, 2020, the actual value of the stock price was 1094.39, while the fitting value was 1196.84, with a difference of -102.45. From February 3, the actual value of the stock price was also different from the fitting value. This may be due to the sudden outbreak of the epidemic, which led to investors' lack of confidence in the financial market, and the financial market fluctuated, thus causing the stock price to fall.

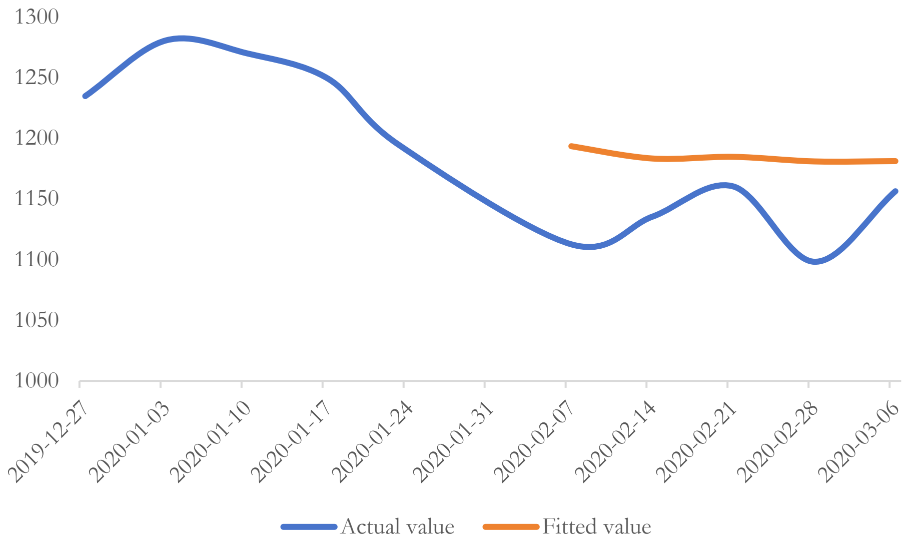

Figure 3. Weekly
Photo credit: Original

Followed by the weekly data (Figure 3), the stock price has a rising stage after February 7, 2020. On February 7, the actual value of the stock price was 1112.62, and the fitting value was 1193.52, with a difference of -80.9. On February 14, the actual value of the stock price was 1135.41, and the fitting value was 1183.38, with a difference of -47.97.

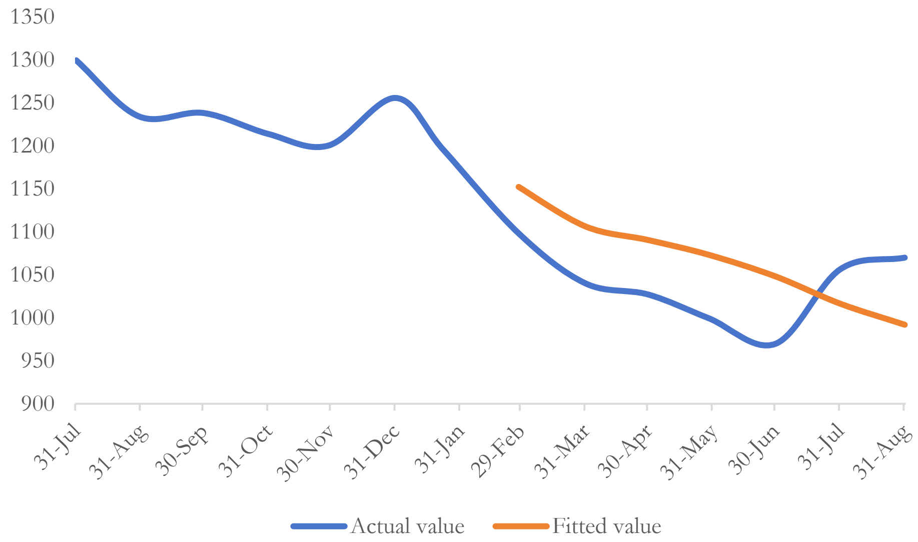

Figure 4. Monthly
Photo credit: Original

Finally, the monthly data shows that the actual value of the stock price on July 31st was 1056.26, the fitting value was 1016.49, and the difference was 36.77, which showed a phenomenon of exceeding the fitting value. This may be due to the successful stabilization of the stock market by the state's continuous policies, and investors have the information about the stock market again, which makes the stock price rise.

4. Discussion

Compared with the existing literature, the critical conclusions obtained by data analysis and research in this paper have both similarities and differences. The similarities are similar to some results of Mzoughi, Ghabri and Guesmi, Aydın and Ari, and the COVID-19 epidemic has impacted the financial market of the energy industry [6, 8]. The difference is that most of the existing literatures are aimed at the global energy industry rather than China. This study mainly studies the impact of epidemic on the financial market of China energy industry. Through this study, we get some enlightenment. The unexpected events such as epidemic have a great impact not only on investors, but also on the financial market. Market instability will lead to stock price fluctuations. This study is meaningful. For policy makers, by understanding this study, we can more intuitively see the impact of the epidemic on the financial market of the energy industry, to introduce some more specific policies to rescue the market. For investors, by understanding this study, it can be more clearly seen that when the country introduced policies, the stock market changed for the better, which can have information about the market and stabilize the investment state.

5. Conclusion

This study mainly studies the impact of epidemic on the financial market of China energy industry. Based on ARIMA model, the change of stock price time series in energy industry is calculated, and the difference between the actual value and the calculated fitting value is compared to judge the change of stock market after the impact of epidemic situation. After being affected by the epidemic, the stock price of China's energy industry first fell, which may be due to the lack of investor confidence, leading to fluctuations in the financial market. Secondly, there has been a slow rise, which may be due to a series of rescue policies, such as monetary policy, to save the precarious stock market.

In a word, the epidemic has had an adverse effect on the financial market of China's energy industry. In order to improve this negative impact and restore investors' information, the government should strive to control the spread of the epidemic and resume production activities appropriately. At the same time, it should be noted that COVID-19 epidemic virus is constantly evolving. Whether there will be a more serious epidemic of COVID-19 epidemic virus in the future, which will have an impact on the market, we need to conduct long-term observation and continuous research in this respect.

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