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The Impact of Major Events on International Oil Prices

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Abstract: As one of the most important energy sources, oil prices in the past 20 years have shown a roller coaster volatility, which seriously threatens the energy strategy security of oil importing countries. By analyzing the law of oil price operation, this paper finds that the peaks and valleys of oil price fluctuations are associated with some major events. In this context, this paper studies and analyzes the characteristics of oil price fluctuations from the perspective of major events. In this paper, BP structural breakpoint test is conducted on the spot price of WTI crude oil during the sample period, and it is found that there are four structural breakpoints in the oil price series during the sample period, and then the sample is divided into five stages. Through the construction of the ARIMA-EGARCH model, the empirical analysis shows that for different stages, only the "911" event in the second stage has no significant impact on oil price volatility, while major events in the other four stages all have significant impact on oil price volatility, among which the COVID-19 epidemic has the greatest impact on oil price volatility. In the long run, in addition to the "911" incident in the United States, major events in the other four stages have a significant impact on oil price volatility. According to the results of model estimation, the information shock curve is made, and it is found that the fluctuation of WTI crude oil spot price is asymmetric.

1. Introduction

In recent years, the impact of major events on the international oil market has all caused fluctuations in international oil prices, and the impact of most of the same types of events generally has similar intensity and duration. Therefore, this paper analyzes the fluctuations of oil prices from the perspective of major events to grasp the historical fluctuations of the oil market.

The major events related to oil contain multiple factors that affect the oil price, and the sudden events will always cause large fluctuations in the oil price. Xun Zhang et al. (2009), based on the structural breakpoint test and the constant return event analysis model, analyzed that the Iranian Revolution, the Gulf War and the Iraq War all had a significant impact on the trend of crude oil prices, and the Iranian Revolution and the Iraq War led to the structural breakpoint of oil prices[1]. Fan and Xu (2011) incorporated dummy variables into the model to study the effects of 911 terrorist attacks and Iraq War on WTI oil prices, and found that the two wars had significant impacts on oil prices [2]. Zavadska M et al. (2020) used the data before 2014 and the GARCH, TGARCH and OLS models, and found that supply and demand disruption events (Gulf War and 911 terrorist attacks in the United States) produced high volatility levels and peaks. Volatility during financial crises (the Asian Financial crisis and the 2008/09 global financial crisis) was more persistent [3]. In April 2020, crude oil prices turned negative for the first time in history, an unprecedented event that has prompted academics to study the impact of COVID-19 on oil price volatility. Devpura N et al. (2020) used hourly data for the first half of 2020 to control for multiple indicators of oil price volatility and found that daily increases in COVID-19 cases and deaths increased oil price volatility by 8% to 22% [4]. Huang et al. (2020) believe that the long-term relationship between crude oil yield volatility and WTI crude oil futures prices has undergone structural changes due to the COVID-19 pandemic [5]. Tarek B et al. (2023) used the ARMA-Spline-GJR model to accurately assess the volatility of WTI crude oil during the COVID-19 pandemic, and found a strong correlation between the COVID-19 pandemic and historical events since 1986 through NIPALS algorithm and PLS-2 regression [6].

Based on the above analysis, BP structural breakpoint test and ARMI-EGARCH model will be used in this paper to test the impact degree and time of major events on oil price fluctuations.

2. Oil price fluctuation stage division

Generally speaking, major events refer to those events that happen suddenly and have a major impact on social security operation or may have a major impact, such as wars, natural disasters, financial crises, epidemics and so on. Based on the research purpose of this paper, the major events in this paper mainly refer to those international major events that cause large fluctuations in oil prices. In different economic environments, events in different periods have different impacts on oil price fluctuations. Therefore, this paper will divide the stages of international oil price fluctuations according to the structural changes of oil prices, and analyze the characteristics of oil price fluctuations in different stages combined with major events.

2.1 Structural breakpoint check

Structural breakpoint test is mainly to determine the time point of structural transformation of time series. The longer the time span of samples used in time series, the greater the possibility of model parameters changing due to major events. After the structural change, the time series before and after the structural change point are regarded as the same trend to analyze, it will not be able to get an accurate conclusion. Identifying and testing the exact time of structural change will help to understand the driving factors of this change and assess the magnitude of the impact of this change (Wang Zhen, 2022)[7]. In this paper, the BP structural breakpoint test method is adopted (Bai and Perron, 2003)[8]. The basic principle is to compute multiple regression models with m breakpoints (or m+1) respectively:

$$
\begin{aligned}
& y_t = z_t{}' \delta + x_t{}' \beta_1 + \mu_t, t = 1, 2, \cdots, T_1 \\
& y_t = z_t{}' \delta + x_t{}' \beta_2 + \mu_t, t = T_1 + 1, \cdots, T_2 \\
& \vdots \\
& y_t = z_t{}' \delta + x_t{}' \beta_{m+1} + \mu_t, t = T_m + 1, \cdots, T
\end{aligned}
\tag{1}
$$

Where y_t is the value of the dependent variable at time t, $z_t(p\times1)$ and $x_t(q\times1)$ are covariance vectors, δ and β are corresponding coefficient vectors, μ_t is the random disturbance term at time t, T is the total sample. The number of breakpoints and the breakpoint date are unknown, and by calculating the residual sum of squares between time series (SSR), the structural change of the horizontal term and the trend term occurs m times at the same time. Then the structural break point can be obtained and the confidence test can be carried out by using BIC criterion to analyze the structure of the global minimization of the sum of residual squares.

The oil price data comes from daily WTI spot price data from the U.S. Energy Information Administration (EIA). BP structural breakpoint test results, RSS and BIS values of oil price series during the sample period (January 2, 1986 to October 2, 2023) are shown in Table 1:

Table 1: BP structure breakpoints test results.

Number	Date					RSS	BIC
0						3898211	84345
1			2008.8.22			2370856	79636
2			2007.10.5	2014.11.13		1224417	73369
3			2006.9.5	2014.9.11	2020.1.8	917210	70645
4		**1999.8.11**	**2006.9.5**	**2014.9.11**	**2020.1.8**	**742331**	**69035**
5	1990.8.21	2001.3.6	2007.2.7	2014.9.11	2020.1.8	742405	69686

2.2 Stage division

According to the results of the structural breakpoint test, the oil price series of the sample period can be divided into five stages, and the major events in the stages are listed, as shown in Figure 1. A descriptive statistical analysis was made of the oil price data in these five periods (Table 2), and the major events involved in the analysis were listed in Table 3.

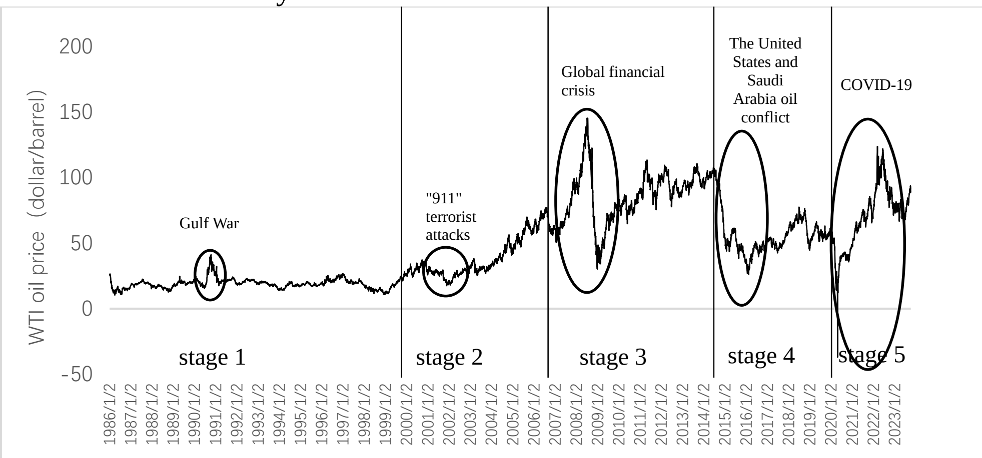

Figure 1: Stage division and corresponding major events.

Table 2: Descriptive statistics.

	Stage1	Stage2	Stage3	Stage4	Stage5
Start-stop time	1986.1.2-1999.8.11	1998.8.12-2006.9.5	2006.9.6-2014.9.11	2014.9.12-2020.1.8	2020.1.9-2023.10.2
Observed number	3452	1767	2019	1335	937
average	18.95	37.86	86.05	54.36	69.39
Standard deviation	3.77	15	19.32	11.13	23.17
Minimum value	10.25	17.5	30.28	26.19	-36.98
Maximum value	41.07	77.05	145.31	95.55	123.64
amplitude	30.82	59.55	115.03	69.36	160.62
Relative amplitude	162.65%	157.29%	133.68%	127.6%	231.47%
Wave intensity	4.71%	8.9%	6.62%	9.56%	24.7%
Coefficient of variation	19.88%	39.61%	22.45%	20.48%	33.38%

Table 3: Major historical events and their periods.

Events	Start date	End date
Gulf war	1990.9.28	1991.4.1
“911” terrorist	2001.9.11	2002.2.8
Global financial crisis	2007.8.29	2009.1.28
The United States and Saudi Arabia oil conflict	2014.9.20	2015.6.10
COVID-19	2020.1.30	2023.5.5

Source: M. I&David R (2022) [9]. Note: In this table, where the WTI crude oil market has historically experienced major events in each row, M. I&David R lists the precise dates (years) when major events caused the crisis in the crude oil market to begin and end, based on the change in the break point. The start and end times of the COVID-19 outbreak come from the date when the World Health Organization declared whether it constituted a PHEIC event.

3. Empirical analysis

3.1 Data selection and pre-processing

In this paper, the daily spot price data of WTI crude oil is selected as the research sample, and the data is from EIA. The sample selection period of this paper is from January 2, 1986 to October 2, 2023, excluding the time point of no transaction, with a total of 9511 sample data. In this paper, EVIEWS10.0 is used to analyze the original data, and the results show that the oil price series is not a stationary series. Therefore, this set of original data is processed by first-order difference, which is more convenient for follow-up research, and this differential data is used to measure the return of WTI crude oil market.

3.2 Models

3.2.1 ARIMA model

The ARIMA model is an extension of the ARMA model. For a non-stationary time series y_t, let y_t be a single integral sequence of order d, y_t~I(d), that is, the non-stationary sequence y_t is converted to a stationary sequence ω_t by D-difference. Major Event variables that affect oil price fluctuations are included in the variable event, including five major international events. "Gulf", "Attack", "World", "Conflict" and "COVID" are used to represent the Gulf War, the "911" incident in the United States, the global financial crisis, the oil conflict between the United States and Saudi Arabia, and the COVID-19 epidemic, introduced as dummy variables.

$$\omega_t = c + \alpha_1\omega_{t-1} + \cdots + \alpha_p\omega_{t-p} + \varepsilon_t + \beta_1\varepsilon_{t-1} + \cdots + \beta_q\varepsilon_{t-q} + \theta Event \quad (2)$$

Where, the parameter c is a constant, $\alpha_1 \ldots \alpha_p$ are the coefficient of the autoregressive model, p is the order of the autoregressive model, ε_t is the random error term, $\beta_1 \ldots \beta_q$ are the moving average model coefficient, and q is the order of the moving average model.

3.2.2 EGARCH model

The GARCH model is commonly used to model financial data, but it assumes that volatility is symmetric. In other words, it assumes that volatility is as likely to increase as it is to decrease. However, volatility tends to be asymmetric during periods of major events. That is, the rate at which volatility is increasing is not consistent with the rate at which volatility is decreasing. If there are asymmetric effects, an asymmetric ARCH model should be established.

For this reason, Nelson (1991) proposed the EGARCH model (exponential GARCH model) [10], which was developed based on this idea. The biggest feature of this model is that it adopts the form of conditional variance logarithm and allows the hypothesis of sum to be more flexible, thus capturing the phenomenon of conditional asymmetry. The conditional variance equation of EGARCH (1,1) is as follows:

$$\ln(\sigma_t^2) = \varphi_0 + \varphi_1 \ln(\sigma_{t-1}^2) + \varphi_2 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + \varphi_3 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{3}$$

The left-hand side of the equation is the logarithm of the conditional variance, which means that the leverage effect is exponential, so the predicted value of the conditional variance must be non-negative. On the right side of the equation φ_2 is the ARCH effect coefficient, φ_3 is the leverage effect coefficient. When $\varphi_3 \neq 0$, it indicates that the impact is asymmetric.

3.3 Empirical results

Table 4: Model fitting results.

Stage1		Stage2		Stage3		Stage4		Stage5		Whole	
Gulf	-0.2083*** (0.0410)	Attack	-0.0122 (0.0427)	World	0.2670*** (0.0821)	Conflict	-0.0691* (0.0940)	COVID	-5.1781*** (0.5136)	Gulf	-0.2782*** (0.0503)
AR(3)	0.8088*** (0.0579)	AR(1)	0.9162*** (0.0247)	AR(1)	0.9368*** (0.0483)	AR(1)	-0.0346* (0.0258)	AR(1)	0.9370*** (0.0382)	Attack	-0.0433 (0.0795)
MA(3)	-0.8395*** (0.0524)	MA(1)	-0.9548*** (0.0184)	MA(1)	-0.9446*** (0.0448)	φ_0	-0.0477*** (0.0095)	MA(1)	-0.8818*** (0.0114)	World	-0.1864** (0.1036)
φ_0	-0.2125*** (0.0108)	φ_0	-0.0769*** (0.0101)	φ_0	-0.0919*** (0.0101)	φ_1	0.9868*** (0.0046)	AR(2)	-0.0732** (0.0341)	Conflict	-0.1103* (0.1275)
φ_1	0.9849*** (0.0026)	φ_1	0.9900*** (0.0027)	φ_1	0.9861*** (0.0035)	φ_2	0.0681*** (0.0131)	φ_0	-0.2436*** (0.0229)	COVID	0.2833*** (0.0385)
φ_2	0.2460*** (0.0115)	φ_2	0.0959*** (0.0124)	φ_2	0.1377*** (0.0143)	φ_3	-0.0388*** (0.0100)	φ_1	0.9850*** (0.0062)	AR(1)	-0.9870*** (0.0104)
φ_3	0.0467*** (0.0058)	φ_3	0.03159*** (0.0090)	φ_3	-0.0439*** (0.0090)			φ_2	0.3441*** (0.0324)	MA(1)	0.9877*** (0.0102)
								φ_3	0.0223* (0.0218)	φ_0	-0.1379*** (0.0037)
										φ_1	0.9877*** (0.0102)
										φ_2	0.1863*** (0.0050)
										φ_3	-0.0025* (0.0027)

Note: The numbers in brackets are standard errors for the estimated coefficients, where ***, ***, and * are significant at the 1%, 5%, and 10% levels.

After a series of tests on the first-order difference series of WTI crude oil spot price in the sample interval and division stage, GARCH model is selected to optimize the mean value equation. Since the volatility caused by shocks is often asymmetric when major events occur, ARIMA-EGARCH model is established for the oil price difference series. In addition, after adding the GARCH model, the partial autocorrelation or moving average coefficient of the mean equation becomes less significant, and the ARIMA model originally set will be adjusted. The model estimation of the whole sample data series shows that the ARIMA-EGARCH model fits well (Table 4).

By making the information impact curve, it is found that "leverage effect" exists. For the first stage, the impact of positive shock on the price fluctuation of WTI crude oil is greater than that of negative shock. For the third and fifth stages and the whole sample, the negative impact on the price fluctuation of WTI crude oil is greater than that of the same amount of positive impact.

4. Conclusion

For different stages, the "911" event in the second stage has no significant impact on oil price volatility, because the event mainly affects the economic development of the United States, but has a weak impact on the global economic development. The COVID-19 pandemic has had the biggest impact on the fifth phase of oil price volatility. In the long run, in addition to the "911" incident in the United States, major events in the other four stages have a significant impact on oil price volatility. The differential sequences of WTI crude oil spot price in the first, third and fifth stages are asymmetrical, but in different directions.

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