Preliminary Research on the Impact of Geopolitical Risks on Crude Oil Prices in the Chinese Market

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Abstract. As an emerging economy, China has maintained a high growth rate in crude oil consumption due to its rapid economic development. The average year-on-year growth rate in the past 30 years is far higher than the overall world average. The listing of SC crude oil futures in Shanghai marks a new stage for the emerging Chinese crude oil market, which also faces various challenges. In today's world, local wars occur from time to time, geopolitical conflicts never stop, and political undercurrents are surging. In such a situation, what kind of impact will the Chinese crude oil market face? How much is the impact of geopolitical risks on crude oil returns and volatility? This has significant practical implications for both investors and policy makers. The impact of geopolitical risks on the returns of China's crude oil market was obtained by attempting to establish a VAR model and further conducting BDS tests on the residual term. The impact relationship is nonlinear and complex.

Keywords: Geopolitical risk, VAR model, BDS test.

1. Introduction

Crude oil is the king of commodities and the cost center of global energy today. Research on crude oil has important economic value and is also a very hot research direction today. In today's world, conflicts continue, and the Russo Ukrainian conflict is still ongoing. The Palestinian Israeli conflict that began in October has entered a white-hot stage of war, with local conflicts such as the Myanmar civil war occurring from time to time. The global geopolitical situation under the Ukraine crisis has undergone significant changes, and energy has become an important bargaining chip for China, the United States, Europe, Russia, and the Middle East in their mediation game. The global oil and gas trade pattern has entered a period of deep adjustment.

As a one-time energy source, the price changes of crude oil have a significant impact on the world economy. For example, in October 1973, the Fourth Middle East War broke out, and Arab members of the Organization of the Petroleum Exporting Countries raised the benchmark crude oil price from $3.01 per barrel to $10.651 to combat Israel and its supporters, triggering the first oil crisis. In this crisis, industrial production in the United States decreased by 14%, industrial production in Japan decreased by more than 20%, and the economies of other industrialized countries also suffered varying degrees of trauma; At the end of 1978, due to political turmoil in Iran and the outbreak of the Iran Iraq War, global crude oil production plummeted and oil prices skyrocketed, leading to the second oil crisis. This crisis caused the Western economy to experience a comprehensive recession for more than half a year in the late 1970s; In August 1990, Iraq suffered from international economic sanctions due to its occupation of Kuwait, resulting in a disruption of crude oil supply and a surge in international oil prices. The third oil crisis broke out, and the United States and Britain quickly fell into a recession. The global GDP growth rate fell below 2% the following year. In summary, the drastic changes in crude oil prices will have a huge impact on global industry and the real economy, thereby affecting people's livelihoods and financial markets. Accurately predicting changes in oil prices is beneficial for the government to timely regulate relevant monetary and fiscal policies, and hedge against international oil price shocks; it is beneficial for investors to adjust their asset portfolio in a timely manner and to some extent avoid investment risks.

Caldara and Iacoviello developed an index in 2018 to measure geopolitical risk. They used 11 important newspapers as news search sources and constructed a monthly geopolitical risk (GPR) index by counting the number of articles related to geopolitical risk each month. Specifically, Caldara and Iacoviello designed six sets of keywords to search for news reports related to geopolitical risks: the first set of keywords includes explicit mention of geopolitical risks, as well as words related to most parts of the world and military tensions involving the United States; The second group consists of keywords directly related to nuclear tensions; The third and fourth groups of keywords respectively contain words related to the threat of war and the threat of terrorism; The fifth and sixth groups of keywords aim to gather reports on actual geopolitical events that can reasonably anticipate an increase in future geopolitical uncertainty. Then, based on the number of articles related to geopolitical tensions each month, calculate their frequency of occurrence, and standardize the average frequency of the decade from 2000 to 2009 to 100 to complete the construction of the monthly GPR index. Caldara and Iacoviello released the GPR index for 19 emerging economies, including China, in 2022.

China officially launched Shanghai crude oil futures in March 2018 and listed them for trading at the Shanghai Energy Trading Center. This indicates that the connection between China's crude oil market and the international market is further strengthened, and international geopolitical risks have a stronger impact on China's crude oil market. Therefore, studying the relationship between these two has certain practical significance.

2. Literature References

Based on the GARCH characteristics of oil price changes, Morana [1] used a semi parametric prediction method based on bootstrapping to predict Brent crude oil prices. The results showed that this prediction method can not only be used to calculate interval predictions of crude oil prices, but also to obtain performance metrics of futures prices. Alquist et al. [2] discussed some key issues in crude oil price prediction, such as the selection of sample periods, crude oil prices and specific models, whether macroeconomic variables can predict actual and nominal crude oil prices, and the importance of crude oil futures markets in crude oil prediction. Yin and Yang [3] used Ordinary Least Squares Regression (OLS) to fit crude oil returns and compared the predictive power of technical indicators and macroeconomic variables on crude oil prices using combination forecasting methods. The results showed that technical indicators showed more significant statistical and economic significance both within and outside the sample. Zhang and Wang [4] used the MIDAS model and high-frequency stock market data to predict low-frequency crude oil prices. The research results showed that high-frequency stock market indicators have more advantages over low-frequency data in monthly crude oil price prediction, and the MIDAS model with high-frequency data is superior to general models. Ma et al. [5] used ordinary least squares regression, Lasso regression, and different combination prediction models to study the effectiveness of big datasets, including uncertainty, market sentiment, macro indicators, and technical indicators, in predicting crude oil. The discovery of uncertainty indicators can more effectively predict fluctuations in crude oil prices, and Lasso regression and combination prediction methods have more significant statistical and economic significance in out of sample forecasting. Zhang et al. [6] used compression estimation methods Lasso and Elastic net to predict crude oil returns using a large number of indicators. The prediction results showed that Lasso and Elastic net models have more significant statistical significance and considerable economic value compared to other prediction models.

The study of geopolitical risk has been a hot topic in recent years, and since Caldara and Iacoviello [7] officially released the Geopolitical Risk Index constructed based on newspaper news, scholars have significantly increased their research on its related papers. Scholars have conducted extensive research on the relationship between the Geopolitical Risk Index and the crude oil market, especially the impact and prediction of geopolitical risk on crude oil prices and returns. Cunado et al. [8] used the TVP-SVAR model to study the dynamic impact of geopolitical risk on international crude oil returns, pointing out that it exhibits a significant negative impact overall, but geopolitical risks related to Middle East tensions have a positive promoting effect on oil prices .Plakandaras et al. [9] explored the predictability of the GPR index on crude oil returns and found that war related GPR indices were the most accurate in predicting short-term returns, while global GPR indices showed higher accuracy in predicting medium to long-term crude oil returns.

3. Organization of the Text

3.1. Data and research methods

3.1.1. Data selection and processing

This section intends to use the VAR model to compare and analyze the impact of 9 types of geopolitical risk indicators on the prediction of Chinese crude oil market prices. The monthly data of Daqing crude oil spot closing prices is selected for research, and the data is sourced from the Wind database. This section uses the Global Geopolitical Risk Index (GPR), Geopolitical Threat Index (GPRT), and Geopolitical Behavior Index (GPRA) proposed by Caldara and Iacoviello (2022) to characterize the international geopolitical risk situation. At the same time, it also introduces the GPR index of China and important import and export countries of Chinese crude oil for comparative research. Among the emerging economies that have released national GPR indices, Russia, Saudi Arabia, and Venezuela are important sources of Chinese crude oil imports, while South Korea and India are the main export targets of Chinese crude oil. Therefore, this article selects the GPR indices of China, India, South Korea, Russia, Saudi Arabia, and Venezuela to reflect the geopolitical risks of China and China's important crude oil import and export countries, which are respectively represented as GPRC_CHN, GPRC_IND, GPRC_KOR, GPRC_RUS, GPRC_SAU, and GPRC_VEN.

All the above GPR indices are monthly frequencies, and the data is sourced from the Geopolitical Risk Index website.

3.1.2. Descriptive statistics

The sample interval is from January 2007 to October 2023. The crude oil yield is calculated using logarithmic yield, and the geopolitical uncertainty index is represented by natural logarithm. Descriptive statistics are shown in Table 1.

Table 1. Descriptive statistics.

variable	frequency	mean value	maximum value	minimum value	standard deviation	Observations
OIL	daily	0.0001	0.2553	-0.3617	0.0262	4163
OIL	monthly	0.0081	0.4082	-0.3829	0.1024	202
GPR	monthly	4.5360	5.7845	4.1043	0.2335	202
GPRA	monthly	4.4112	5.5427	3.3481	0.3296	202
GPRT	monthly	4.5919	6.0232	3.9726	0.3027	202
GPRC_CHN	monthly	3.9923	5.5452	3.0445	0.4974	202
GPRC_IND	monthly	2.8966	4.4886	1.7918	0.4462	202
GPRC_KOR	monthly	3.1926	5.2040	1.7918	0.6522	202
GPRC_RUS	monthly	4.2996	6.7991	3.0910	0.6624	202
GPRC_SAU	monthly	2.9216	4.4998	1.3863	0.6325	202
GPRC_VEN	monthly	1.4127	3.9512	0.0000	0.8066	202

As shown in Table 1, among the three global indicators, the mean and maximum values of geopolitical threats are the highest, while the mean and maximum values of geopolitical actions are the lowest. This is because Caldara and Iacoviello proposed a geopolitical risk index based on six sets of self-designed keywords, where the geopolitical threat index includes the first four sets of keywords: the first set of keywords includes explicit mention of geopolitical risk, as well as words related to most parts of the world and military tensions involving the United States, and the second set of keywords directly related to nuclear tensions, The third and fourth groups of keywords respectively contain words related to the threat of war and the threat of terrorism; And geopolitical actions include the last two key words: both are reports on actual geopolitical events that have occurred. On the surface, the geopolitical threat index includes keywords with stronger impact and higher risk factors, so its quantitative index is also higher.

3.2. Stationarity test

The VAR model requires all sequences to be stationary time series. In order to avoid false regression in subsequent analysis of the time series, this paper conducts stationarity tests on the variables. In practical applications, the ADF test is a commonly used unit root test method. Therefore, this article uses the ADF method to perform stationarity tests on the selected time series. The null hypothesis of the ADF unit root test is that the sequence has a unit root.

This article uses the ADF unit root test method to determine whether a variable is stationary, and the test results are shown in Table 2.

Table 2. The ADF unit root test.

variable	ADF statistic	1%critical value	5%critical value	10%critical value	P value	result
OIL (daily)	-9.5989	-3.4629	-2.8757	-2.5744	0.0000	stable
OIL (monthly)	-9.5990	-3.4629	-2.8758	-2.5744	0.0000	stable
GPR	-6.0008	-3.4629	-2.8757	-2.5744	0.0000	stable
GPRA	-5.5087	-3.4629	-2.8757	-2.5744	0.0000	stable
GPRT	-4.1874	-3.4629	-2.8757	-2.5744	0.0009	stable
GPRC_CHN	-3.6044	-3.4631	-2.8758	-2.5744	0.0065	stable
GPRC_IND	-3.5461	-3.4634	-2.8759	-2.5745	0.0078	stable
GPRC_KOR	-3.9954	-3.4631	-2.8758	-2.5744	0.0018	stable
GPRC_RUS	-3.3334	-3.4631	-2.8758	-2.5744	0.0147	stable
GPRC_SAU	-4.2601	-3.4632	-2.8758	-2.5745	0.0007	stable
GPRC_VEN	-3.3554	-3.4634	-2.8759	-2.5745	0.0138	stable

The ADF unit root test results indicate that among all tests, variables OIL, GPR, GPRA, GPRT, and GPRC_ CHN, GPRC_ IND, GPRC_ KOR and GPRC_ The probability of SAU being less than 1% rejects the original hypothesis, while GPRC_ RUS and GPRC_ The probability of VEN being less than 5% rejects the original hypothesis, indicating that the sequences are all stationary time series and meet the conditions for constructing a VAR model.

As the data has already been processed, the crude oil yield has been calculated using a logarithmic rate of return, and the geopolitical uncertainty index has been expressed as a natural logarithmic growth rate. The subsequent processing will remain consistent and will not be explained one by one. Since all variables are of order 0, cointegration testing is not necessary.

3.3. Granger causality test

Considering that the Granger causality test results depend on the order of lag, this paper tests the Granger causality relationship between different geopolitical uncertainty indices and crude oil returns under 1-3 orders of lag, as shown in Table 3.3. It was found that only India's GPR is the Granger cause of OIL, while others accept the original hypothesis. Granger causality test is used to determine whether there is a causal relationship between two time series variables. It makes judgments based on whether a variable can provide additional information about the past value of another variable. The Granger causality test is based on time series data and infers by comparing the impact of one variable on another at different time points. So, the experimental results indicate that the GPR index is not the reason for the change in crude oil returns.

Table 3. Granger causality test.

Null Hypothesis	Lag 1st order		Lag 2nd order		Lag 3rd order	
	f-statistics	P value	f-statistics	P value	f-statistics	P value
GPR does not Granger Cause OIL	0.0000	0.9959	0.4927	0.6118	0.5049	0.6794
GPRA does not Granger Cause OIL	0.9037	0.3430	0.6798	0.5079	0.6696	0.5716
GPRT does not Granger Cause OIL	0.4930	0.4834	0.8542	0.4272	0.6743	0.5688
GPRC_CHN does not Granger Cause OIL	0.7124	0.3997	0.4996	0.6076	0.8834	0.4507
GPRC_KOR does not Granger Cause OIL	0.0261	0.8719	0.3327	0.7174	0.1806	0.9095
GPRC_IND does not Granger Cause OIL	3.7444*	0.0544	2.1232	0.1224	1.7280	0.1626
GPRC_RUS does not Granger Cause OIL	0.0364	0.8489	2.0742	0.1284	2.0127	0.1135
GPRC_SAU does not Granger Cause OIL	0.0586	0.8090	0.6618	0.5171	0.4395	0.7250
GPRC_VEN does not Granger Cause OIL	0.5278	0.4684	0.7842	0.4579	1.1316	0.3375

Note: ***, **, * respectively indicate significant at the 1%, 5%, and 10% levels.

The VAR model studies the intrinsic correlation between multivariate sequences, while Granger causality further illustrates the sequential guidance relationship between multivariate sequences. So even if the one-way Granger causality test results in GPR index not being the cause of changes in crude oil returns, establishing a VAR model for research still has certain significance.

3.4. Estimation results of VAR model

This chapter constructs nine bivariate VAR models with different GPR indices and crude oil returns. To ensure the accuracy of the results, it is necessary to first confirm the lag order of the VAR model to avoid bias in the model estimation results. This article tests the lag order using LR, FRF, AIC, SC, HQ and other criteria, and finds that most models should choose lag order 1.

The results indicate that the lagged terms of GPR and OIL have a significant impact on themselves, but when using monthly data of the same frequency, the coefficient of GPR's impact on OIL is not significant, that is, the predictive effect is not significant. Therefore, using same frequency data may lead to distorted results.

The results indicate that the impact of the GPR index on the returns of the Chinese crude oil market is not significant. However, Cunado et al. used the GPR index to study the dynamic impact of geopolitical risk on international crude oil returns, pointing out that it exhibits a significant negative impact overall. However, geopolitical risk related to the Middle East tension has a positive promoting effect on oil prices. The GPR index has a significant impact on international crude oil returns, but its impact on Chinese crude oil returns is not significant. There may be two reasons for this impact:

The first reason may come from its own transmission mechanism. Li et al. (2021) found that geopolitical risk has a significant heterogeneity in the impact of different types of crude oil price fluctuations, with a stronger impact on Brent crude oil; Yang et al. (2023) found through a non-parametric quantile causal test method based on wavelet multi resolution that the impact of geopolitical risk on the crude oil futures market has obvious asymmetric characteristics, and the impact on crude oil returns is more pronounced at the extreme quantile. This indicates that the impact of GPR factor on the returns of China's crude oil market is much smaller than that of international crude oil (such as WTI, Brent crude oil, etc.), and only when facing major geopolitical conflicts (such as the outbreak of the Russo Ukrainian conflict, the Israeli Palestinian conflict, etc.) will it be greatly impacted.

The more important reason may be that the impact of geopolitical risks on crude oil prices is not linear, so this article will extract the residual of the VAR model for BDS testing.

3.5. BDS test

In 1987, scholars such as Bmck invented the BDS test, which can be used to test whether sequence $\{r_t: t = 1,2,\ldots,T\}$ is independent and identically distributed. The null hypothesis can be written as:

H_0: Sequence $\{r_t\}$ is independently identically distributed

The definition of associated integral is as follows:

$$C(N,m,\delta) = \frac{2}{N(N-1)}\sum_{t<s} H(\delta - \|r_t^m - r_s^m\|) \tag{1}$$

In equation, $N = T - m + 1$, $H(\varphi) = \begin{cases} 0, \varphi \le 0 \\ 1, \varphi > 0 \end{cases}$, $H(\varphi)$ is equivalent to an indicative function. The equation is mainly used to calculate the probability that the distance between two embedding vectors r_t^m and r_s^m is less than δ.

Construct BDS statistics:

$$BDS(m,\delta) = \frac{\sqrt{T}[C(N,m,\delta) - C(N,1,\delta)^m]}{\hat{\sigma}_m(\delta)} \tag{2}$$

In equation, $\hat{\sigma}_m(\delta)$ is an estimate of the asymptotic standard deviation of $C(N,m,\delta) - C(N,1,\delta)^m$.

If H_0 holds, then $BDS(m,\delta) \sim N(0,1)$. When the critical value u_α for m,δ and significance level α is determined, and the absolute value of statistic $BDS(m,\delta)$ is smaller than u_α, then H_0 is accepted, that is, sequence $\{r_t: t = 1,2,\ldots,T\}$ is considered to be an independent and identically distributed sequence.On the contrary, as long as the absolute value of $BDS(m,\delta)$ statistic is greater than u_α, H_0 is rejected, indicating that the sequence $\{r_t: t = 1,2,\ldots,T\}$ is not independently and identically distributed.

It is worth noting that the BDS test results using monthly data of Daqing crude oil are not good and there is a problem of distortion. Therefore, this section of the BDS test uses the daily closing price of Daqing crude oil spot, that is, daily data, for testing. Similarly, in order to maintain the same frequency, the Geopolitical Risk Index also uses daily data, which is also sourced from the Geopolitical Risk Index website.

A VAR model was established with the logarithmic growth rate of the daily frequency data of the geopolitical risk index as the independent variable and the daily closing price return of Daqing crude oil as the dependent variable. The residual was subjected to BDS test, and the results of the BDS test are shown in Table 4.

Table 4. BDS test.

	2	3	4	5
OIL (daily)	1.587**	2.479**	2.702***	2.734***

Note: ***, **, * respectively indicate significant at the 1%, 5%, and 10% levels.

According to the BDS test results, it can be concluded that for different nested dimensions, all residuals reject the null hypothesis of independent and identically distributed at a significance level of 5%, indicating a significant nonlinear dynamic trend between geopolitical risk and Daqing crude oil returns.

3.6. Further Discussion

In the naive perception of most investors in the market, the view that geopolitical factors can cause global crude oil prices to rise seems to have been widely accepted: on the one hand, it is because geopolitical events in major oil producing countries (especially the Middle East) can easily affect regional crude oil production and transportation, thereby triggering supply tension in the global crude oil market and driving up oil prices; On the other hand, the two global oil crises triggered by geopolitical factors in the 1970s and 1980s, as well as the high oil prices brought about by the Gulf War and the Iraq War, left a deep impression on the market. However, the naive view that such geopolitical factors will inevitably drive-up global crude oil prices may seem reasonable, but it is not entirely correct. The market has also begun to notice that although geopolitical events have occurred frequently since 2010 (especially 2014), the impact on global crude oil prices seems to be not as significant as expected. Changes in global crude oil prices do not always follow geopolitical events and sometimes even experience reverse changes, which is inconsistent with past perceptions.

The reason may be that many geopolitical events only pose potential threats and do not constitute a substantial impact on crude oil supply. Since 2010 (especially 2014), the frequency of geopolitical events has increased, but these geopolitical events are more of a potential threat and do not directly affect crude oil supply. Although it may raise global crude oil prices in the short term, when the market realizes that this potential threat to crude oil supply will not actually occur, market concerns will be alleviated, and oil prices will naturally quickly fall back to normal levels, so there will be no significant response to such threatening geopolitical events.

Another more direct proof is that the frequency of geopolitical events that led to practical actions from the 2003 Iraq War to early 2014, as well as from 2014 to the present, has been continuously decreasing, resulting in relatively less disturbance to oil prices. Secondly, some geopolitical events themselves have little to do with global crude oil supply and demand, such as the Paris terrorist attacks in June 2015 and the North Korean incident in June 2017, and therefore do not constitute a substantial disturbance to oil prices. In addition, there are also some geopolitical events that can even drag down global crude oil prices. Two typical cases are the 9/11 attacks in the United States in September 2001 and the Crimean events in the second half of 2014. The former affected US economic growth expectations and suppressed global crude oil demand and prices, while the latter reflected the sanctions imposed by Western countries led by the United States on Russia, The United States chooses to increase crude oil production to lower global oil prices and suppress Russia.

It can be seen that the impact of geopolitical risks on crude oil price returns, including the Chinese crude oil market, is very complex.

4. Summary

For the research on the impact of geopolitical risks on the returns of China's crude oil market, this article uses a vector autoregressive model and finds that it cannot explain the direct relationship between the two. However, from a practical perspective and other literature analysis, there must be a connection between the two. The BDS test results also prove that the impact of geopolitical risks on the returns of China's crude oil market is complex and nonlinear, this is consistent with the conclusions drawn by many scholars studying the returns of the international crude oil market.

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References

[1] Morana C. A semiparametric approach to short-term oil price forecasting [J]. Energy Economics, 2001, 23(3):325-338.

[2] Alquist R, Kilian L, Vigfusson R J. Forecasting the price of oil [J]. Handbook of Economic Forecasting, 2011, 2:427-507.

[3] Yin L, Yang Q. predicting the oil prices: Do technical indicators help? [J]. Energy Economics, 2016, 56(5): 338-350.

[4] Zhang Y, Wang J. Do high-frequency stock market data help forecast crude oil prices? Evidence from the MIDAS models [J]. Energy Economics, 2019, 78(2):192-201.

[5] Ma F, Liu J, Wahab M, Zhang Y. Forecasting the aggregate oil price volatility in a data rich environment [J]. Economic Modelling, 2018, 72: 320-332.

[6] Zhang Y, Ma F, Wang Y. Forecasting crude oil prices with a large set of predictors: Can LASSO select powerful predictors? [J]. Journal of Empirical Finance, 2019, 54:97-117.

[7] Caldara D, Iacoviello M. Measuring Geopolitical Risk. Working Papers -- US Federal Reserve Board's International Finance Discussion Papers[R]. February 2018:1-47.

[8] Cunado J, Gupta R, Lau CKM, Sheng X. Time-Varying Impact of Geopolitical Risks on Oil Prices [J]. Defence & Peace Economics.2020; 31(6):692-706.

[9] Plakandaras V, Gupta R, Wong W-K. Point and density forecasts of oil returns: The role of geopolitical risks [J]. Resources Policy. 2019,62:580-587.