The Russian-Ukraine Conflict, Crude Oil Price Fluctuation, and Dynamic Changes in China's and American Manufacturing

Biao Wang

Department of Economics, SUNY at Albany, New York, the U.S.

bwang5@albany.edu

Abstract. This study examines how responsive the manufacturing indices of China and the United States are to changes in the price of WTI crude oil over the three months prior to and following the Russian-Ukrainian Conflict, paying particular attention to changes in the manufacturing index brought on by volatile oil prices. To assess the static and dynamic effects of changes in crude oil prices on the manufacturing indices in China and the US, this study uses a time series model. The use of a VAR(p) model to clearly correlate WTI crude oil price volatility with the Russian-Ukrainian Conflict is the distinguishing feature. The empirical results demonstrate a strong correlation between the size of China's and the US manufacturing index's oscillations in response to geopolitical shocks. Both countries' manufacturing indices are highly susceptible to changes in WTI crude oil prices.

Keywords: Geopolitical conflict; oil price volatility; manufacturing index; VAR modeling.

1. Introduction

As one of the factors of industrial production, the fluctuation of oil price has an impact on industrial production. Over the past six months, a number of factors have come together to push the price of crude oil to almost record levels. And the cost of manufacturing and transportation is increased by high energy prices. The rise of international crude oil prices leads to the rise of industrial production costs, which leads to the rise of the cost of the whole industry chain and thus leads to the macroeconomic downward economic situation such as inflation. For now, the war between Russia and Ukraine was the biggest factor pushing crude oil prices higher.

The potential impact of the war between Russia and Ukraine on the manufacturing industry happens in two ways: the impact of the war and the destruction of manufacturing capacity and the impact on trade and production following sanctions. It strongly disrupted the production and trade of international bulk commodities, including grains, crude oil, and fertilizers. Wheat costs have increased by about 112 percent in the past 12 months, while corn, soybean, and vegetable oil costs have also increased by about 80 percent [1]. Due to the fact that Russia and Ukraine are major exporters of those kinds of bulk commodities and the war has halted normal trade between these two nations as well as the import and export restrictions put in place by governments, the price of bulk commodities and crude oil will rise in the short term, adding more uncertainty and concern to the current situation, but in the long term with the likelihood that the war will end, the price of bulk commodities and crude oil could shift tow.

Furthermore, it is important to consider the long-term effects of changes in the price of oil on the industrial sector. More people are beginning to understand the impact that potential changes in the oil market will have on the industrial industry. According to Takuji Fueki, in comparison to actual supply and demand shocks, long-term aggregate demand shocks and expected future oil supply shocks have a substantial impact. Future shocks to supply and demand can be blamed for about 23% of the fluctuation in crude oil prices over a 12-month period [2]. However, only a few types of literature investigate this subject from the perspective of rising crude oil prices, and now, available research mostly concentrates on the macro and industrial levels to investigate the influence of variations in the price of crude oil on the manufacturing index.

This paper aims to fill the gap in the relationship between the fluctuation of oil prices and the manufacturing industries in China and the United States by examining the effects of the global crude oil price fluctuation caused by the Russia-Ukraine conflict on the research of manufacturing indices of China and the United States.

Although oil is a key strategic resource and the price elasticity of demand is modest, the government frequently views it as a significant political weapon. As a result, numerous geopolitical events or tensions invariably upset the oil market, and extreme geopolitical events frequently result in investor panic and abnormal volatility in the oil market [3]. The VAR model is used in this study to examine how changes in crude oil prices affect the returns of the Chinese and American manufacturing industries. The GARCH model is used to examine how these changes affect volatility. Both the Chinese and American manufacturing industries are examined, along with the macroeconomic effects of these changes over the short- and long-term. In order to research the impacts of fluctuations in the price of crude oil on the manufacturing industries in China and the United States, the author analyzes present oil price shocks and forecasts future oil price shocks to the manufacturing industry index. The mechanisms by which oil price volatility affects industrial development and the effects of these shocks on industrial output in the United States and China are then revealed. These effects are based on scientific research that suggests expectations of oil supply and demand play a key role in oil price volatility. The analysis of changes in global crude oil prices and manufacturing performance in China and the United States not only fills a research need in this area, but it also provides a solid micro-empirical basis for the development of macroeconomic policy for the present and the future. Giving industrial companies advise on how to justly and successfully avoid the external risk caused by changes in the price of crude oil globally is useful. The recommended model has a close relationship to the research on VAR model analysis for oil prices, which is discussed in the literature review that follows.

There has been a lot of research done on how oil price shocks affect the industrial industry. The ability of China's whole manufacturing sector to manufacture goods efficiently would unquestionably be severely hampered by the growth in global oil price volatility, according to Cheng Dong's research [4]. Each shock has a unique impact on how much the globe produces, according to Takuji Fueki's research [5]. Jinyu Chen and Xuehong Zhu's research indicates that China's industrial PPI suffers when oil prices increase due to supply shocks, but that both the industrial PPI and oil prices increase due to overall market volatility and fuel demand shocks that behave similarly [6]. From a macroeconomic view, the impact of variations in crude oil prices on the growth of China's manufacturing industry as a whole. Milani made the point that an increase in the price of crude oil in the global market would have an impact on both the supply and demand for the commodity, resulting in inflation. The more a country's economy depends on oil, the more significant the inflation, and the more of an impact on the industrial sector there is from changes in oil prices [7].

Much research in this field has looked at the examination of oil price volatility. More precisely, according to John Chatziantoniou, Michail Filippidis, George Filis, and David Gabauer, increased realized oil price volatility, particularly in the short term, can be attributed to changes in oil supply and demand, oil inventories, and uncertainty in the financial markets [8]. Bourghelle, Jawadi, and Rozin claim that the conflict between the major oil-producing nations resulted in a demand shock that decreased demand for crude oil globally, increased volatility, and led to severe economic depression in the majority of industrialized and developing nations [9].

Most academics also ignore the link between regional wars and oil price changes, notably the link between oil price changes and geopolitical conflicts in the context of time series. In addition, earlier research on the correlation between manufacturing indexes and oil prices tended to ignore the medium-term and long-term effects of oil price variations in favor of concentrating on the immediate effects on the manufacturing index. Thus, this paper will analyze the dynamic relationship between oil price volatility caused by geopolitical conflicts and the manufacturing index in the framework of time series.

The remaining portions of this essay are divided into four pieces. The methodology including the VAR model and ARMA-GARCH model will be briefly introduced in section 2, section 3 will analyze the primary empirical findings, section 4 will discuss the findings of this study and section 5 will conclude.

2. Methodology

2.1 Data source

This study intends to shed light on how the fluctuation in oil prices affected the manufacturing index during the Russia-Ukraine conflict. Thus, the author uses daily data over the period November 2021 to May 2022 (starting 3 months before Russia and Ukraine war).

This data sample is used to study the fluctuation in oil prices from November 2021 to the ongoing conflict between Russia and Ukraine. Using daily data (closing prices) to record important details and track the development of the oil prices. For the oil data, the author used the West Texas Index (WTI) as a benchmark for oil prices.

2.2 Unit Root Test

The ARMA model is built using the unit-root test as a foundation. The unit root test is used to determine whether a sequence contains a unit root. The outcome is a non-stationary time series, which is demonstrated by the presence of the unit root. Regression analysis will produce false regression if the unit root exists in the sequence, indicating that the process is unstable. Therefore, the unit root test is required to guarantee the sequence's stability.

$$x_t = c_t + \beta x_{t-1} + \sum_{i=1}^{p-1} \phi_i \triangle x_{t-i} + e_t \quad (1)$$

Rules of decision-making in this paper are using the ADF test, which can show the result with more accuracy. The augmented Dickey-Fuller (ADF) statistic for the test has an unfavorable value. The assumption that there is a unit root at a particular level of confidence is strongly rejected the more negative it is [10, 11]. In the test, the null hypothesis H_0: β=1, and the alternative hypothesis H_1: $\beta < 1$.

$$ADF\ Test = \frac{\hat{\beta}-1}{standard\ deviation\ of\ \hat{\beta}} \quad (2)$$

The method of the unit root test in this paper is to define the null hypothesis H_0 as unstable and test the probability value through ADF to compare whether the null hypothesis is rejected or not, to achieve the purpose of the unit root test for sequence stationarity.

2.3 VAR Model

The Vector Autoregressive (VAR) model, which allowed for the dependency of a variable on both its lagged values and those of other explanatory factors, was used to analyze the interdependence between time series.

The author uses the following three-dimensional VAR to model the dynamics of oil price volatility.

Set three time series variables $\{y_{1t},\ y_{2t} y_{3t}\}$, as the explained variables of the three equations, respectively. The explanatory variables are the m-order lag values of these three variables, making a ternary VAR (3) model:

$$\begin{cases} y_{1t} = \beta_{10} + \beta_{11} y_{1,t-1} + \cdots + \beta_{1p} y_{1,t-p} + \gamma_{11} y_{2,t-1} + \cdots + \gamma_{1p} y_{2,t-p} + \varepsilon_{1t} \\ y_{2t} = \beta_{20} + \beta_{21} y_{1,t-1} + \cdots + \beta_{2p} y_{1,t-p} + \gamma_{21} y_{2,t-1} + \cdots + \gamma_{2p} y_{2,t-p} + \varepsilon_{2t} \\ y_{3t} = \beta_{30} + \beta_{31} y_{1,t-1} + \cdots + \beta_{3p} y_{1,t-p} + \gamma_{31} y_{2,t-1} + \cdots + \gamma_{3p} y_{2,t-p} + \varepsilon_{3t} \end{cases} \quad (3)$$

To predict the model parameters with accuracy, the variables in a VAR model must be stationary.

2.4 ARMA-GARCH model specification

The method is expanded by the author by including two extra variables in the ARMA-GARCH model, which enables identifying shocks in the price of international crude oil to forecast the volatility of the manufacturing index in the future.

The expression of ARMA model is as follow:

$$x_t = \phi_0 + \sum_{i=1}^{m} \phi_i x_{t-i} + a_t - \sum_{i=1}^{n} \theta_i a_{t-i} \quad (4)$$

Where ϕ_0 is constant term, order *m* and order *n* are non-negative integers, x_t is the daily WTI crude oil price, the order *m*'s auto-regressive component's variable is ϕ_i, θ_i is the moving average component of order *n*'s parameters, and a_t is the error term.

The derivation of MA is as follows:

$$x_t = \phi_0 - \theta_1 x_{t-1} - \theta_1^2 x_{t-2} - \theta_1^3 x_{t-3} - \cdots + a_t \quad (5)$$

Where *i*≥1, satisfied $\phi_i = -\theta_1^i$, if want the model to be stationary series, the absolute value of θ_1 must be smaller than 1, because $|\theta_1| < 1$, thus, when $i \to \infty$, $\theta_1^i \to 0$, the contribution of x_{t-i} to x_t decays exponentially as *i* increase.

$$x_t + \theta_1 x_{t-1} + \theta_1^2 x_{t-2} + \cdots = \phi_0 + a_t \quad (6)$$

Then, x_{t-i} can be expressed as:

$$x_{t-1} + \theta x_{t-2} + \theta_1^2 x_{t-3} + \cdots = \phi_0 + a_{t-1} \quad (7)$$

Times θ_1 on both sides of the equation (7), then minus equation (6):

$$x_t = \phi_0(1 - \theta_1) + a_t - \theta_1 a_{t-1} \quad (8)$$

This equation shows that in addition to the constant term, x_t is the weighted average of the two perturbation terms a_t and a_{t-1}. Therefore, MA model is white noise stationary series.

It is generally accepted that time-series data frequently exhibit autocorrelation while cross-sectional data are more likely to exhibit heteroscedasticity, namely "Autoregressive Conditional Heteroskedasticity" (Autoregressive Conditional Heteroskedasticity), denoted as ARCH.

For the general form of the linear regression model:

$$y_t = x_t'\beta + \varepsilon_t \quad (9)$$

Where the conditional variance of the perturbation term ε_t is $\sigma_t^2 \equiv Var(\varepsilon_t|\varepsilon_{t-1}, \dots)$, the subscript t of σ_t^2 indicates that the conditional variance can change over time. Inspired by the phenomenon of volatility agglomeration, the hypothesis σ_t^2 depends on the disturbance term's square during the prior period:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \quad (10)$$

For using the MLE to estimate ARCH model, estimate both the original equation ($y_t = x_t'\beta + \varepsilon_t$) and conditional variance equation ($\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2$) at the same time.

In comparison to the ARCH model, the GARCH model is more frugal because it uses fewer parameters [12-14]. The GARCH model is divided into two parts: the mean equation ($y_t = x_t'\beta + \varepsilon_t$)

and the variance equation $(\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2)$. The GARCH (*p*, *q*) model has the following general form:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_q\varepsilon_{t-q}^2 + \gamma_1\sigma_{t-1}^2 + \cdots + \gamma_p\sigma_{t-p}^2 \tag{11}$$

Where the most commonly used GARCH model is GARCH (*1*, *1*):

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \gamma_1\sigma_{t-1}^2 \tag{12}$$

3. Empirical results

3.1 VAR order identification

"LL" means log-likelihood. "LR" means likelihood-ratio test (likelihood ratio tested for the joint significance of the last order coefficients). Where if use "LR" as the standard, the VAR level should be ordered 11.

Table 1. VAR model identification

Lag	LL	LR	df	p
0	797.722			
1	802.686	9.9286	9	0.356
2	809.006	12.641	9	0.180
3	816.772	15.532	9	0.077
4	828.316	23.088	9	0.006
5	836.179	15.726	9	0.073
6	845.596	18.833	9	0.027
7	855.503	19.814	9	0.019
8	859.484	7.9627	99	0.538
9	866.487	14.006	9	0.122
10	873.202	13.429	9	0.144
11	883.438	20.472*	9	0.015
12	889.419	11.963	9	0.215

According to the estimation in Table 1, it can be determined that the order of VAR is 11. And the stability of order 11 is confirmed in the stability test in Figure 2.

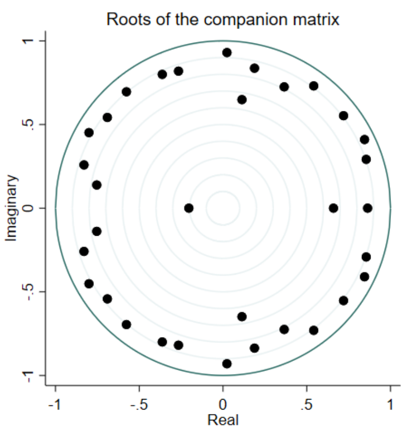

Fig. 1 VAR stability

In the expression of VAR(*p*) model as follows, where $\{\varepsilon_t\}$ is the vector white noise process.

$$y_t = \Gamma_0 + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \varepsilon_t \tag{13}$$

Define three $np \times 1$ column vector as follows:

$$\widetilde{y_t} = \begin{pmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{pmatrix}_{np\times 1}, \widetilde{\Gamma_0} = \begin{pmatrix} \Gamma_0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}_{np\times 1}, \widetilde{\varepsilon_t} = \begin{pmatrix} \varepsilon_t \\ 0 \\ \vdots \\ 0 \end{pmatrix}_{np\times 1} \tag{14}$$

Define the $np \times np$ companion matrix as follows:

$$\tilde{\Gamma} = \begin{pmatrix} \Gamma_1 \Gamma_2 \cdots \Gamma_p \\ \mathrm{I}_n \; 0 \cdots 0 \\ \vdots \;\; \vdots \qquad \vdots \\ 0 \;\; 0 \; \mathrm{I}_n \; 0 \end{pmatrix}_{np\times 1} \tag{15}$$

Where can write equation (13) in VAR (1) form as follows:

$$\widetilde{y_t} = \widetilde{\Gamma_0} + \tilde{\Gamma}\widetilde{y_{t-1}} + \widetilde{\varepsilon_t} \tag{16}$$

Thus, the stationarity of VAR(p) model requires that all eigenvalues of its adjoint matrix $\tilde{\Gamma}$ fall within the unit circle.

3.2 Impulse and response

Where the equation means that when the disturbance term ε_{jt} of the j variable in the t period increases by one-unit (while other variables and the disturbance terms of other periods are unchanged), and the number i variable in the $(t+s)$ phase influence on the value $y_{i,t+s}$. Considering $(\partial y_{i,t+s}/\partial \varepsilon_{jt})$ as a function of the time interval s, is the "impulse response function" (*IRF*).

$$\frac{\partial y_{t+s}}{\partial \varepsilon_t'} = \Psi_s \tag{17}$$

Figure 2 demonstrates a positive standard deviation of international crude oil prices single-period impulse response process of shocks to the U.S. manufacturing index and the Chinese manufacturing index.

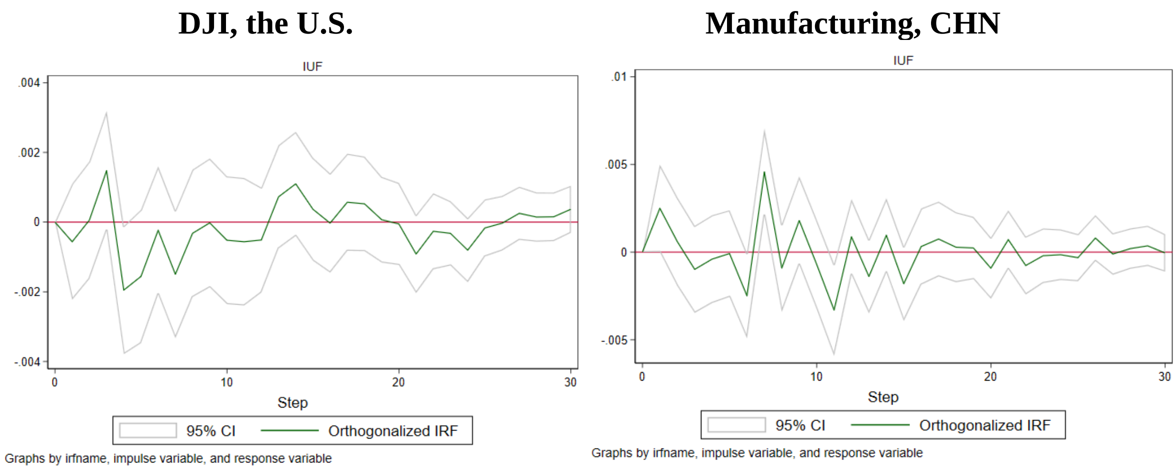

Fig. 2 Impulse and response

The green line is the point estimation result of the pulse response, and the gray line is the 95% confidence interval of the pulse response point estimate result. Because this paper uses daily data, the horizontal axis represents the day.

From the graph can intuitively see that during the first ten days of the Russia-Ukraine conflict, the manufacturing index of China and the United States fluctuated with the sharp fluctuations of international crude oil prices, but as time passes, the fluctuations brought by crude oil prices tend to stabilize, and the manufacturing index tends to develop smoothly.

3.3 ARMA identification

Autocorrelation Function (ACF) is a set of autocorrelation coefficients $\{\rho_\kappa\}$.

Where ρ_κ defined as:

$$\rho_\kappa = \frac{Cov(x_t,x_{t-k})}{\sqrt{Var(x_t)Var(x_{t-k})}} \frac{Cov(x_t,x_{t-k})}{Var(x_t)} = \frac{\gamma_\kappa}{\gamma_0} \tag{18}$$

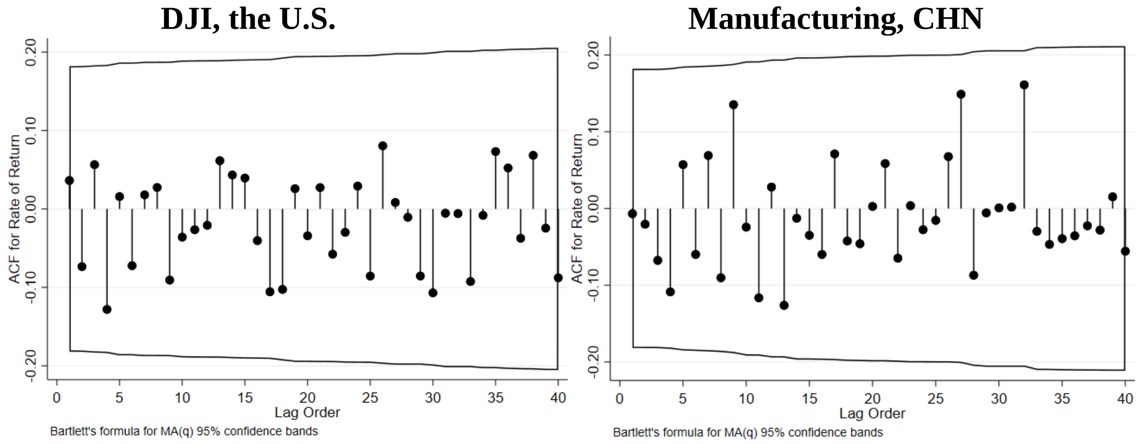

Fig. 3 ACF for MA identification

According to ACF estimation, yield of DJI and China's manufacturing index have no significant autocorrelation.

The partial autocorrelation function (PACF) in analysis provides the cointegration relationship between time series data. When analyzing data to determine the amount of lag in autoregressive models, this function is crucial. $AR(p)$ model or extended $ARIMA(p,q,d)$ the model can be determined by drawing part of the autocorrelation function [15].

$$x_t = \phi_0 + \phi_1 x_{t-1} + \cdots + \phi_p x_{t-p} + a_t \tag{19}$$

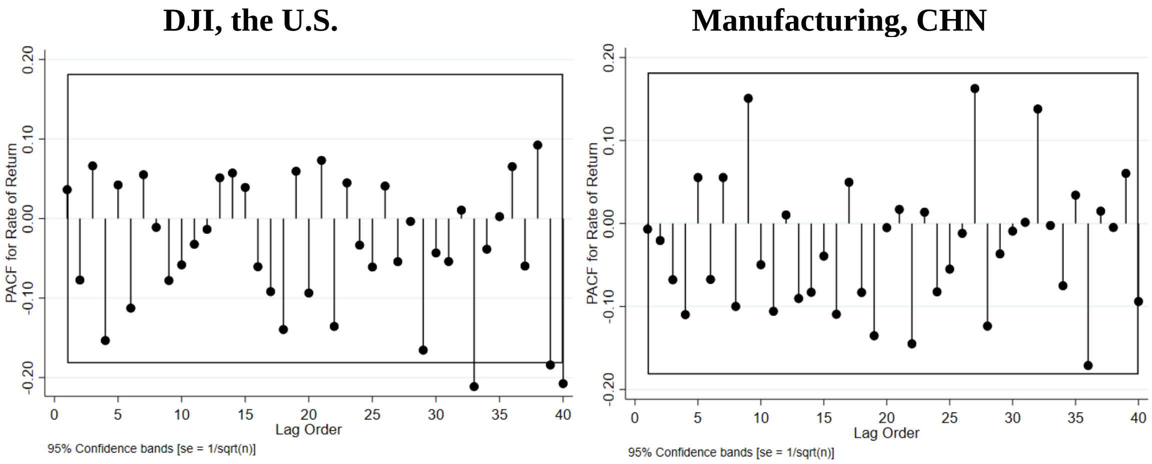

Fig. 4 PACF for AR identification

DJI: Large spike at lag 33, otherwise a damped wave with intermittent positively and negatively correlations.

Manufacturing, CN: Large spike at lag 36, followed by a damped wave with alternating positive and negative correlation.

3.4 ARMA-GARCH estimation results

From the estimation result of the variance equation, the increase in international crude oil price did not cause the intraday fluctuation of the Dow Jones index and China manufacturing index.

Table 2. ARMA-GARCH model estimation results

Variables	(1) DJI		(2) Manufacturing, CN	
	Coef.	Std. err	Coef.	Std. err
Crude oil	5.3184	4.0853	-11.3386*	21.5764
ARCH (-1)	-0.0416	0.0570	-0.1785**	0.0816
GARCH (-1)	-0.3887	0.2999	-0.7071***	0.1464
Constant	0.0004	0.0010	0.0019*	0.0012

4. Discussion

This research advances the macroeconomic and manufacturing impacts of price changes of international crude oil on the manufacturing sectors in China and America to the micro-manufacturing level and adds regional political and military conflicts as the influencing factor, partially making up for the shortcomings of earlier studies' microanalysis. In this work, the time series model is also employed to describe the static and dynamic effects of changes in crude oil prices on the manufacturing indices in China and America.

Given that the Russia-Ukraine conflict and other unpredictable and volatile events continue to affect crude oil markets, policymakers and authorities should assess and put in place the proper limits to prevent rapid and disproportionate changes in oil prices brought on by geopolitical worries. Also, the fluctuation of oil prices caused by the Russia-Ukraine conflict will weaken the overseas market demand, reduce the driving effect on the economic growth of China and the United States, and directly increase the supply side risk of the manufacturing industry. The continued rise in international prices of crude oil, agricultural products, non-ferrous finance, and other commodities will increase cost pressure on the manufacturing industry and trigger the risk of an overall decline in the manufacturing industry [16].

The Conflict between Russia and Ukraine severely dampened investor confidence and greatly reduced the investment willingness of multinational companies, which will be a severe challenge to China's manufacturing industry. International capital demand for safe haven, resulting in emerging market funds to accelerate the return to the U.S. market, will bring a respite for the U.S. manufacturing industry. On the basis of this analysis, future studies can investigate into how additional risks or unknown factors relate to the world's crude oil markets.

5. Conclusion

Concerns regarding the relationship between the manufacturing sector and crude oil markets have grown as a result of the conflict between Russia and Ukraine, which has exacerbated financial and geopolitical uncertainty in the energy markets. By utilizing a VAR model based on daily data, this study contributed to the existing of research about the relationship between the manufacturing industry index and WTI crude oil price.

According to the analysis, there is a strong linear relationship between the manufacturing industry index and oil prices. Due to the oil market's sensitivity to changes brought on by outside shocks and the close relationship between the crude oil price index and the manufacturing index, crude oil is an essential raw material for manufacturing businesses. Thus, investors should take equivalent action when geopolitical risk rises to lessen the loss of volatility crude oil brings and moderate the dramatic swings in the global oil market.

References

[1] Cmpeanu V. The Effects of The War in Ukraine – The Global Food Crisis Becomes More Real. Euroinfo, 2022, 6.

[2] Fueki T, Nakajima J, Ohyama S, et al. Identifying oil price shocks and their consequences: The role of expectations in the crude oil market. International Finance, 2020.

[3] Huang Jianbai, Ding Qian, Zhang Hongwei, Guo Yaoqi, Suleman Muhammad Tahir. Nonlinear dynamic correlation between geopolitical risk and oil prices: A study based on high-frequency data. Research in International Business and Finance,2021,56.

[4] Cheng D, Zheng W P, Jian Y U. Oil Price Fluctuations and the Performance of China's Manufacturing Firms. Journal of Central University of Finance & Economics, 2019.

[5] Chen Jinyu, Zhu Xuehong. The Effects of Different Types of Oil Price Shocks on Industrial PPI: Evidence from 36 Sub-industries in China. Emerging Markets Finance and Trade, 2019, 57(12).

[6] Filis G, Degiannakis S, Floros C. Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. International Review of Financial Analysis, 2011, 20(3): 152-164.

[7] An Yuxing, Tian Hua. The impact of international crude oil price fluctuations on the development of China's manufacturing industry. Price Monthly, 2020(10): 27-31. DOI: 10.14076/j.issn.1006-2025.2020.10.04.

[8] Chatziantoniou Ioannis, Filippidis Michail, Filis George, Gabauer David. A closer look into the global determinants of oil price volatility. Energy Economics, 2021 (prepublish).

[9] Bourghelle David, Jawadi Fredj, Rozin Philippe. Oil Price Volatility in the context of Covid-19. International Economics, 2021 (prepublish).

[10] Fuller W A. Introduction to Statistical Time Series ~John Wiley and Sons. 1976.

[11] Ghani I, Rahim H A. Modeling and Forecasting of Volatility using ARMA-GARCH: Case Study on Malaysia Natural Rubber Prices. IOP Conference Series: Materials Science and Engineering, 2019, 548(1): 012023 (13pp).

[12] Briand, Hill G/, Carter R. Using Excel for Principles of Econometrics.

[13] Poon S H, Granger C. Forecasting Volatility in Financial Markets: A Review (revised edition. SSRN Electronic Journal, 2002.

[14] Engle R. Dynamic Conditional Correlation. Journal of Business & Economic Statistics, 2002, 20(3): 339-350.

[15] Robinson P M. Testing for strong serial correlation and dynamic conditional heteroskedasticity in multiple regression. Journal of Econometrics, 1991, 47(1): 67-84.

[16] Jiménez-Rodríguez, Rebeca, M Sánchez. Oil price shocks and real GDP growth: empirical evidence for some OECD countries. Applied Economics, 2005, 37.