Cryptocurrency under Local Conflict: Evidence from Soaring Crude Oil Price

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Abstract. The ongoing Russian invasion of Ukraine is signaled as a black swan event with major effects to the world. The consequence of the corresponding sanctions sparked short-term and long-term damages not only to the countries directly involved but also to the global economy. Namely, the soaring crude oil price pushes countries to economic crisis. Additionally, the emergence of the cryptocurrency becomes a centerpiece in this conflict, as Ukraine opens cryptocurrency donations and Russia tries to avoid sanction with cryptocurrency. The relationship between the traditional Crude oil market and the relatively new global market of cryptocurrency has sparked this paper to research the effect of this local conflict. In this paper, Crude Oil yields, Bitcoin yields, and Ethereum yields from June 2021 to Sep 2022 are extracted. VAR model and ARMA-GARCHX model are selected to analyze the data. This study intends to examine the relationship between the oil yields and the major cryptocurrency yields, namely Bitcoin and Ethereum, with hopes to forecast the corresponding cryptocurrency yield followed by an oil yield shock.

Keywords: Cryptocurrency, Russian Invasion, Crude oil.

1. Introduction

On February 24, 2022, Russian starts the invasion of Ukraine marking the major escalation between two nations' conflict. Western nations introduced one of the strongest sanctions in century. This paper takes focus of the sanction regarding Russian oil export. Russia was the world's third largest oil produced. In Jan 2022, Russia produced 10 million barrels per day (mb/d) of crude oil and exported 5Mb/d of crude oil in Dec 2021 [1]. Prior to the conflict, Europe imports about 30% of its oil from Russia [2]. After the phase out period of 6 to 8 months proposed in the sanction, Europe will completely ban importation of crude oil and refined petroleum products from Russia [3]. With fear of short supply, the price of oil has risen over $100/barrel for the first time since 2014 [4].

Oil price hikes undoubtedly affects the entire global market of all economic entities. For instance, the consumer price index (CPI) in US has been rocketing and triggering the inflation. Then the Federal Reverse System (FED) increases the federal interest rate in response, resulting chain reactions to all financial markets. In this paper, the analysis of this oil price shock to newer market like cryptocurrency could be of interest.

Although the decentralized cryptocurrency isn't on the sanction list, it has taken the spotlight, nonetheless. The Ukrainian government officially accepted donation in cryptocurrency and received over $100 million [5]. On the other hand, the fear to Russia using crypto services to avoid sanctions has also emerged [6]. After major exchanges like Binance, Coinbase, and Kraken ensured compliance with sanction, the nature of cryptocurrencies still made the situation misty. In the end, the continuing exposure of cryptocurrencies gave major coins like Bitcoin and Ethereum a strong bounce back after the conflict occurred.

There're reported or unrecognized effects on the cryptocurrency price through out the Russian-Ukraine conflict. In comparison, the oil market is more well-known with most open data published. Hence, this paper will focus on the effect of soaring oil price to major cryptocurrencies, Bitcoin and Ethereum.

Previous research has found connections between the price of bitcoin and oil. Comparing Bitcoin to gold, cryptocurrency is valued as a hedge option or a haven for oil [7]. Chancharat and Butda

conducts research using Diagonal BEKK-GATCH model to fit the Bitcoin and oil price [8]. As a result, some model strategies can be of use.

Additionally, the consequence of the war has seen significant damage to the economy, especially to the countries heavily supplying oil. According to the book published by the World Bank Group, Syria civil war, starting in 2011, has shifted Syria's net exports of oil towards a net import of oil in 2012, following a continuing negative GDP growth [9]. It may take 10 to 20 years for Syria to recover to pre-war real GDP level in 2010. Russia has similar dependence of oil towards its economy and this conflict has tremendous cost underlying. This paper takes the inspiration of the connection between war and oil, and further examine the oil market around the time span of the Russian-Ukraine conflict.

The COVID19 pandemic has changed the world decisively, especially to the monetary policies set by various countries in response to the economic crisis. There has been researches about the relationship between the COVID outbreak and the cryptocurrency market. The paper published by Iqbal, Fareed, Wan, and Shahzad concluded the asymmetric association between COVID19 and cryptocurrency's return [10]. Similar to the Russian-Ukraine conflict, the global incident towards cryptocurrency market inspires this paper. Further discovery of the cryptocurrency market during an uncertainty market and a black swan event can be of interest.

The rest of this paper is organized as follows: Part 2 explains the research design with information about the data source, data stability, and the explanation of financial and statistical models used. Part 3 continues with a detailed discussion of the results of VAR model and ARMA-GARCHX model, including a forecast using impulse function. After that, based on the model estimates, part 4 presents further discussion around the implementation and strategies for policy makers and traders. Lastly, part 5 draws the conclusion.

2. Research Design

2.1. Data Source

This paper extracted daily closing price of Brent Crude Oil ETF from Jun.1, 2021 to Sep. 9, 2022, from Investing.com [11]. The timeframe is selected to cover the Russian invasion of Ukraine starting on Feb. 24, 2022, along with historic data of oil price 8-month before the conflict till the present. Bitcoin and Ethereum are unlike to traditional exchange-trade fund (ETF), because there doesn't exist market closing for crypto-currencies. To align with the Brent Crude Oil ETF, the closing price for Bitcoin and Ethereum at each calendar day is recorded from investing.com, with dates of non-trading period omitted. For example, Sep. 4, 2022 was a weekend with no trading and no price for Brent Crude Oil ETF, the closing prices of Bitcoin and Ethereum on Sep. 4 were omitted from the dataset. Stata is used to further analyze the collected dataset.

2.2. Augmented Dickey-Fuller (ADF) Test

$$D_t = c_t + \beta D_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta D_{t-i} + e_t \quad (1)$$

Augmented Dickey-Fuller (ADF) test is a unit root test to determine whether the dataset is stationary [12]. Equation (1) explains the model. The null hypothesis is $\beta = 1$ while the alternative hypothesis is $\beta < 1$. It's assumed that there exists a unit root under the null hypothesis, hence the dataset is nonstationary.

Table 1. ADF test

Variables	t-statistic	p-value
	Price	
BTC	-1.833	0.6886
ETH	-1.753	0.7270
Brent	-2.149	0.5188
	Yield	
BTC	-13.043	0.0000***
ETH	-13.190	0.0000***
Brent	-13.776	0.0000***

Based on the result from ADF test in Table 1, p-values for price variables are too high and fail to reject the null hypothesis. The model with price variable is nonstationary. As a result, further augmentation on the variable is necessary. Yield rate is calculated based on the price difference between dates. P-values for yield variables appears to be significant at 0.01 level and rejects the null hypothesis. The findings shows that the above-mentioned yield series doesn't contain a unit root and dataset with yield rate is stationary.

2.3. Vector Autoregression (VAR) model

A vector autoregression (VAR) model is often used to capture the relationship with itself and other variables over a period of time [13]. This paper is set to analyze a relationship between three different variables, yield rates of oil price, Bitcoin price, and Ethereum price.

$$y_{1t} = \alpha_1 + \beta_{11}y_{1,t-1} + \cdots + \beta_{1p}y_{1,t-p} + \gamma_{11}y_{2,t-1} + \cdots + \gamma_{1p}y_{2,t-p} + \delta_{11}y_{3,t-1} + \cdots + \delta_{1p}y_{3,t-p} + e_{1t} \quad (2)$$

$$y_{2t} = \alpha_2 + \beta_{21}y_{1,t-1} + \cdots + \beta_{2p}y_{1,t-p} + \gamma_{21}y_{2,t-1} + \cdots + \gamma_{2p}y_{2,t-p} + \delta_{21}y_{3,t-1} + \cdots + \delta_{2p}y_{3,t-p} + e_{2t} \quad (3)$$

$$y_{3t} = \alpha_3 + \beta_{31}y_{1,t-1} + \cdots + \beta_{3p}y_{1,t-p} + \gamma_{31}y_{2,t-1} + \cdots + \gamma_{3p}y_{2,t-p} + \delta_{31}y_{3,t-1} + \cdots + \delta_{3p}y_{3,t-p} + e_{3t} \quad (4)$$

Under this context, equation (2) is set to forecast the three time series variables: oil yield, Bitcoin yield, and Ethereum yield, $\{y_{1t}, y_{2t}, y_{3t}\}$, written as a set of linear equation. For instance, the oil yield for time t ,y_{1t}, includes terms: α_1 as the constant, $\beta_{11}y_{1,t-1} + \cdots + \beta_{1p}y_{1,t-p}$ as the past p lags of oil yields, $\gamma_{11}y_{2,t-1} + \cdots + \gamma_{1p}y_{2,t-p}$ and $\delta_{11}y_{3,t-1} + \cdots + \delta_{1p}y_{3,t-p}$ as the past lags of Bitcoin yields and Ethereum yields respectively, e_{1t} as the noise term.

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \gamma_{11} & \delta_{11} \\ \beta_{21} & \gamma_{21} & \delta_{21} \\ \beta_{31} & \gamma_{31} & \delta_{31} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \beta_{1p} & \gamma_{1p} & \delta_{1p} \\ \beta_{2p} & \gamma_{2p} & \delta_{2p} \\ \beta_{3p} & \gamma_{3p} & \delta_{3p} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-p} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} \quad (5)$$

$$\boldsymbol{y_t = \Gamma_0 + \Gamma_1 y_{t-1} + \quad + \Gamma_p y_{t-p} + \varepsilon_t} \quad (6)$$

Equation (2) can be rewritten in the matrix form to equation (5). Further simplification concludes the classic VAR (p) model shown in equation (6).

2.4. ARMA-GARCHX Model

2.4.1 Autoregressive Moving Average (ARMA) Model

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i \, y_{t-i} + a_t - \sum_{i=1}^{q} \theta_i \, q_{t-i} \quad (7)$$

ARMA model, Equation (7), consists of two parts: an Autoregressive AR (p) model, $\phi_0 + \sum_{i=1}^{p} \phi_i \, y_{t-i}$, and a Moving Average MA (q) model, $a_t - \sum_{i=1}^{q} \theta_i \, q_{t-i}$. In short, AR model uses past autocorrelation to forecast, while MA model uses past impulse response for white noise to forecast. In combination, ARMA model factors both past values and white noise errors.

2.4.2 Generalized Autoregressive Conditionally Heteroscedasticity (GARCH) Model

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_q\sigma_{t-q}^2 \quad (8)$$

The ARCH model, $\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_p\varepsilon_{t-p}^2$, was firstly introduced in 1982 by Robert Engle to better modeling the market by counting volatility clusters and recognize the presence of heteroskedasticity [14]. In 1986, Tim Bollerslev extended ARCH to a GARCH model, shown in equation (8), to include an autoregressive term of σ_t^2 itself [15]. GARCH (p, q) further optimize the forecast accuracy by reducing the estimating parameters in original ARCH (p) model.

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 B_t + \gamma_2 B_{t-1} + \gamma_3 B_{t-2} \quad (9)$$

Equation (9) explains the simpler GARCH (1, 1) model with exogenous input variable B. GARCH (1, 1) has been wildly used in financial time series modelling. GARCH (1, 1) is selected in this paper to value the spillover effect of oil market to cryptocurrency market.

In conclusion, ARMA model counts the mean, while GARCH model values the conditional variance.

3. Empirical Results and Analysis

3.1. Order of VAR Model

To determine the lag order of the VAR model, Likelihood-ratio (LR) test is used. When the Likelihood-ratio appears significant and the corresponding p-value is low enough (marked by asterisk sign, *), the desired lag order is concluded.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	1869.99				1.1E-09	-12.1233	-12.1088	-12.087
1	1872.87	5.7729	9	0.762	1.1E-09	-12.0836	-12.0255	-11.9383
2	1876.05	6.3561	9	0.704	1.2E-09	-12.0458	-11.9441	-11.7915
3	1879.56	7.0244	9	0.635	1.2E-09	-12.0101	-11.8649	-11.6468
4	1885.39	11.658	9	0.233	1.2E-09	-11.9896	-11.8007	-11.5172
5	1889.62	8.4651	9	0.488	1.3E-09	-11.9586	-11.7262	-11.3773
6	1895.97	12.684	9	0.177	1.3E-09	-11.9413	-11.6653	-11.251
7	1902.86	13.795	9	0.13	1.3E-09	-11.9277	-11.6081	-11.1284
8	1906.52	7.3033	9	0.606	1.4E-09	-11.893	-11.5298	-10.9847
9	1911.98	10.937	9	0.28	1.4E-09	-11.87	-11.4633	-10.8527
10	1915.65	7.3417	9	0.602	1.5E-09	-11.8354	-11.3851	-10.7091
11	1919.68	8.0585	9	0.528	1.5E-09	-11.8031	-11.3092	-10.5679
12	1923.44	7.5022	9	0.585	1.6E-09	-11.7691	-11.2316	-10.4248
13	1927.11	7.3471	9	0.601	1.6E-09	-11.7345	-11.1534	-10.2812
14	1928.95	3.6795	9	0.931	1.7E-09	-11.688	-11.0633	-10.1257
15	1930.79	3.6833	9	0.931	1.8E-09	-11.6415	-10.9732	-9.97022
16	1935.48	9.3705	9	0.404	1.8E-09	-11.6135	-10.9016	-9.8332
17	1946.43	21.906	9	0.009*	1.8E-09	-11.6262	-10.8707	-9.73689
18	1951.36	9.8705	9	0.361	1.9E-09	-11.5998	-10.8008	-9.60149
19	1958.19	13.647	9	0.135	1.9E-09	-11.5856	-10.743	-9.47836
20	1960.06	3.7556	9	0.927	2.0E-09	-11.5394	-10.6532	-9.32312
21	1965.63	11.138	9	0.266	2.0E-09	-11.5171	-10.5874	-9.19184
22	1974.01	16.753	9	0.053	2.0E-09	-11.5131	-10.5397	-9.0788
23	1979.15	10.28	9	0.328	2.1E-09	-11.488	-10.4711	-8.94474
24	1985.24	12.18	9	0.203	2.2E-09	-11.4691	-10.4086	-8.81684

In Table 2, p-value for lag 17 appears to be below 0.01, hence the desire lag order is 17.

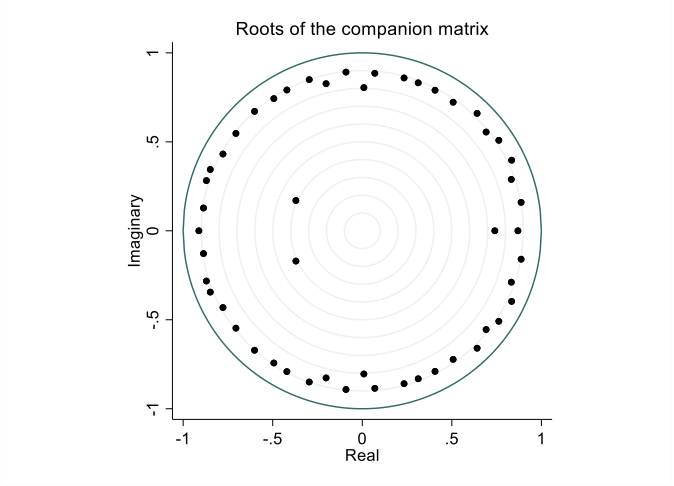


Figure 1. VAR stability (Photo credit: Original)

After the estimation of VAR model, it's necessary to determine whether the residuals are autocorrelated and follow a normal distribution. Lastly, to confirm VAR model condition of stability, eigenvalues are graphed in Figure 1. There's indication that all the values are well inside the unit circle, hence VAR (17) model in this paper is stable.

3.2. Impulse Response

$$\frac{\partial y_{t+s}}{\partial \varepsilon_t'} = \psi_s \tag{10}$$

Impulse Response Function (IRF), as shown in equation (10), presents the response of variables in y in period of $t+s$ to a shock in time t [16]. $\frac{\partial y_{t+s}}{\partial \varepsilon_t'}$ will be plotted as IRF for all s. In this paper, the investigation on Bitcoin and Ethereum price yields responding to shocks from oil price yields is conducted and s = 30 are selected.

BTC ETH

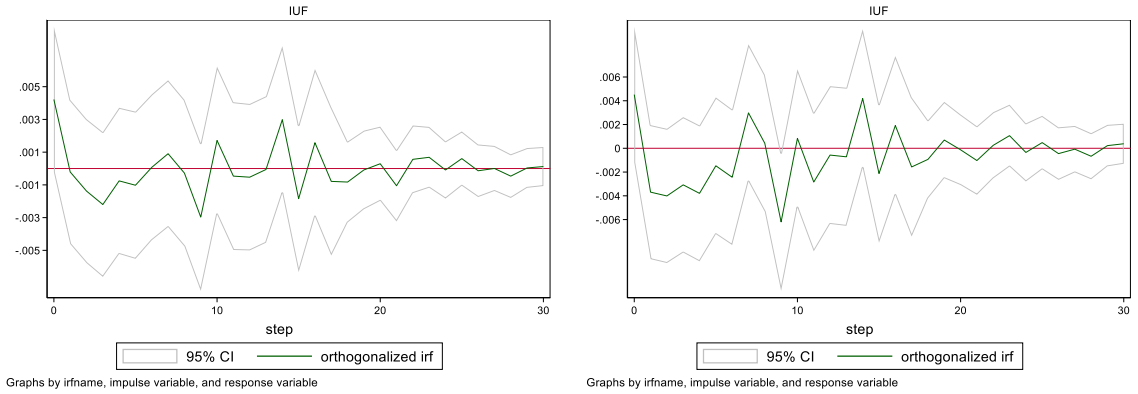


Figure 2. Impulse and response (Photo credit: Original)

From the estimated result of IRF, Figure 2, the oil price hike trigged by Russian-Ukraine conflict results fluctuation in cryptocurrency market. In detail, if Brent oil yields increase by 1% at t=0, the corresponding Bitcoin yields and Ethereum yields are affected by 0.4%. Then the shock maintains the fluctuation of the market over the next few terms in the future. In addition, from Figure (2), the fluctuation rage is wilder for Ethereum yields after the shock of oil yield happened. This could be due to the smaller market size for Ethereum comparing to Bitcoin.

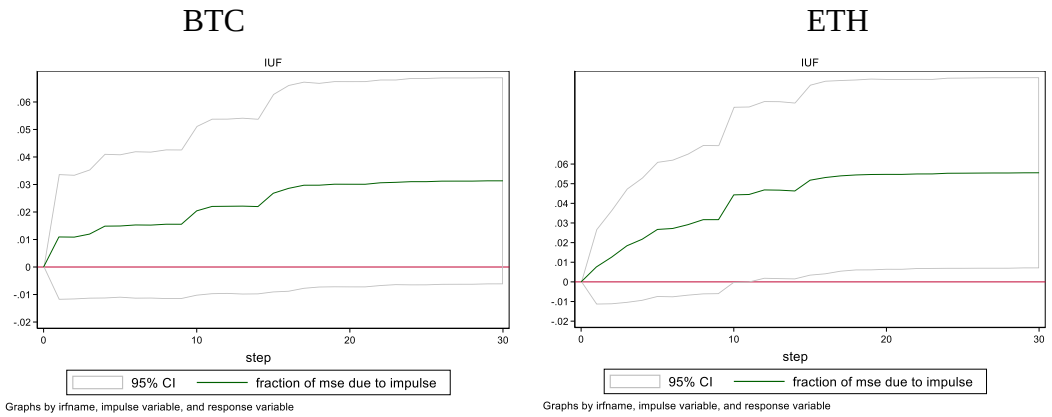


Figure 3. Cumulative response (Photo credit: Original)

There're limitations to determine the net impact or the cumulative impact of the oil yield shock through the impulse and response plot along. Hence, this paper further conducts the Cumulative Impulse Response Function. As shown in Figure 3, cumulative response function reflects the oil yield shock at the current period to the cumulative impact of the future 30 terms of Bitcoin and Ethereum yields. In conclusion, the cumulative impact for Bitcoin yields is around 3%, and 5% for Ethereum.

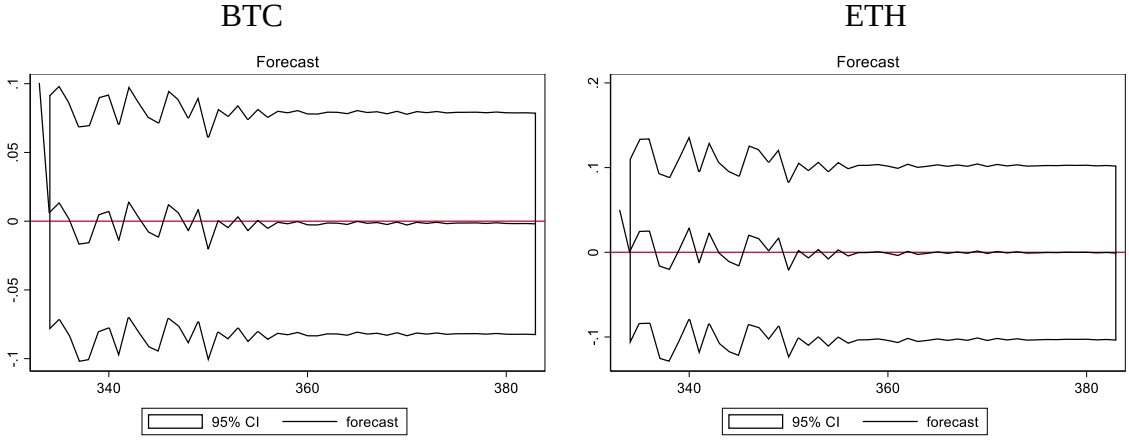


Figure 4. Forecast (Photo credit: Original)

Moreover, based on the entire VAR model, including the autocorrelation in cryptocurrency market, this paper presents the forecast of Bitcoin and Ethereum yields. As shown in Figure 4, Bitcoin yield is likely to perform similarly to Ethereum yield: from an initial positive yield to a fluctuation around 0%.

3.3. ARMA Specification

PACF and ACF plots, Figure 5, are used to determine the lag value of MA (p) and AR (q) models for Bitcoin and Ethereum yields in this paper [17].

For the ARMA Bitcoin model, the first notable spikes are at lag of 5, hence ARMA (5, 5) model would likely be feasible, with value p is 5 and the value q is also five. For ARMA Ethereum model, ARMA (5, 5) would likely also be feasible with p as 5 and q as 5.

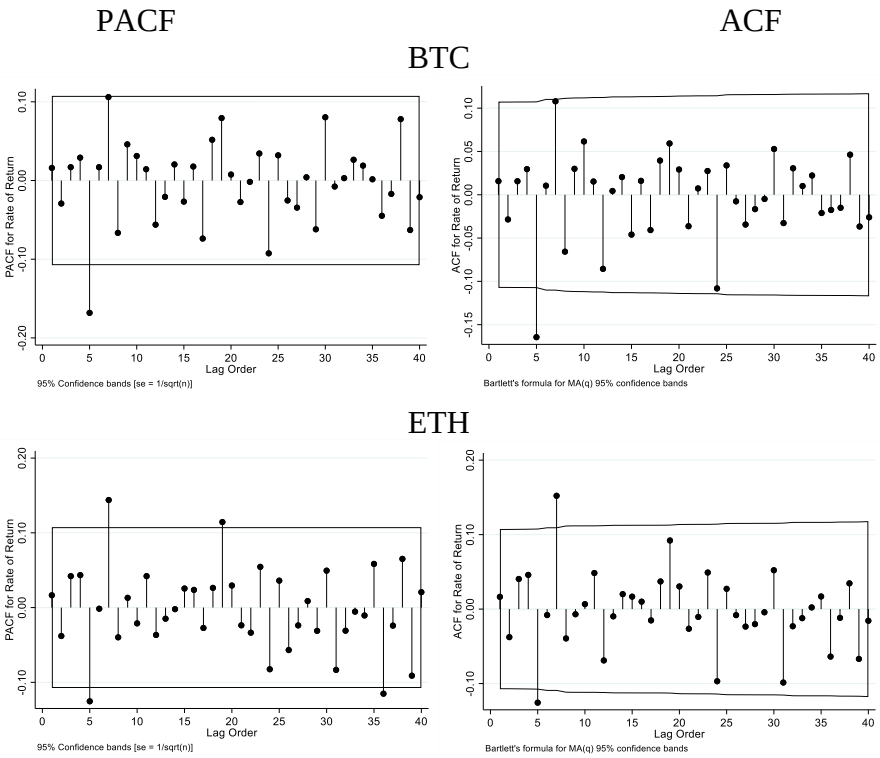


Figure 5. PACF and ACF (Photo credit: Original)

3.4. ARMA-GARCHX Estimation Results

Table 3 presents the ARMA-GARCHX estimation results for Bitcoin yields. Because the maximum likelihood estimation for Ethereum yields doesn't converge during the data simulation, this paper won't report the model regarding Ethereum yields.

From the table, the estimation results from row (1) to row (3) show p-value greater than 0.1 in ARCH and GARCH. In detail, after the estimation equation controls autocorrelation and moving average effect, bitcoin yield doesn't appear statistically significant heteroscedasticity. Hence, the basic condition for a GARCH model is unsatisfied. In addition, from the exogenous input estimation, the current periods and future periods of Brent oil yield don't appear to affect the fluctuation on Bitcoin yields.

Overall, this paper couldn't conclude the effect from oil price yield shocks to the fluctuation on Bitcoin and Ethereum yield.

Table 3. ARMA-GARCH-X estimation results

	(1)		(2)		(3)	
	Coef.	p>|Z|	Coef.	p>|Z|	Coef.	p>|Z|
			Mean equation			
AR, L5	-.4349	0.104	-.4371	0.101	-.4525	0.094
MA, L5	.2718	0.348	.2696	0.351	.2899	0.324
Constant	-.0016	0.475	-.0017	0.446	-.0019	0.401
			Variance equation			
			Brent			
L0	-5.1995	0.245	-5.0810	0.395	-5.6728	0.237
L1			-.3059	0.960	.9475	0.883
L2					3.0276	0.594
			GARCH (1, 1)			
ARCH	-.0289	0.367	-.0290	0.371	-.0282	0.462
GARCH	.1800	0.744	.1697	0.845	.3848	0.365
Constant	-6.4513	0.000***	-6.4389	0.000***	-6.7411	0.000***

4. Discussion

In comparison of other studies, this paper takes the focus on the yields of Bitcoin and Ethereum price after the impulse from the oil yield, while existing articles commonly discuss price correlation between cryptocurrency and oil. The difference of the chosen parameters presents a detailed and stabilized option to fit the dataset to existing economical and statistical models.

Through this paper, ARCH and GARCH models have proved unfit to examine the effects of oil price yield to cryptocurrencies. The homoscedasticity of bitcoin yield and the divergency on maximum likelihood estimates for Ethereum limit the use of ARCH and GARCH models.

On the other hand, the VAR model successfully accounts the impulse effect. There're questions and warnings by policy markers regarding the evasion of sanctions to Russia through cryptocurrencies. In addition to the fact that large exchanges and crypto wallets are pausing services in Russia, the VAR model also forecast a fluctuated yield returning to 0% after the shock. Hence, Russian influence on the cryptocurrency market is limited.

Existing articles explains that investors can use Bitcoin and Ethereum as hedge options or safe havens for oil price movements. This paper concludes that cryptocurrencies are good hedge options in short term as they tend to have a cumulative response of 3% and 5% respectively with strong response at the initial periods, and cryptocurrencies are safe havens in long term against oil movement since the yield rates of Bitcoin and Ethereum tend to return to 0% after the impulse.

5. Conclusion

The object of this paper is to study how local conflicts affect the oil price and eventually the potential impact on cryptocurrencies. A detailed VAR model including the order determination process and the impulse response functions is introduced for this purpose. Additionally, an ARMA-GARCHX model assessing Bitcoin price yield with oil price yield as exogenous inputs is also introduced. However, the unsatisfied condition results the unfitness of ARMA-GARCHX model. Ethereum yield fails to converge on maximum likelihood estimation, hence unfit to use ARMA-GARCHX model as well.

With empirical investigations, this paper concludes that conflicts and sanctions can cause oil price hikes, and such shocks affect the cryptocurrencies market only in short term. More Specifically, both Bitcoin and Ethereum yields increase by 0.4% with oil price increasing 1%. There's a positive correlation in short term. Furthermore, there's not enough evidence to suggest a long-term affect on cryptocurrencies price or yields by an oil price impulse.

References

[1] IEA. Oil market and Russian supply – Russian supplies to global energy markets – analysis [EB/OL]. IEA, 2022. [2022-10-18]. https://www.iea.org/reports/russian-supplies-to-global-energy-markets/oil-market-and-russian-supply-2.

[2] FAULCONBRIDGE G, LIGHT F. Russia blames Europe for gas crisis, warns west of oil retaliation [EB/OL]. Russia blames Europe for gas crisis, warns West of oil retaliation, Reuters, 2022. [2022-10-17]. https://www.reuters.com/business/energy/kremlin-europe-is-blame-nord-stream-1-shutdown-2022-09-05/#:~:text=Russia%20is%20the%20world's%20second,its%20consumers'%20soaring%20energy%20bills.

[3] COUNCIL OF THE EUROPEAN UNION. EU sanctions against Russia explained [EB/OL]. Council of the European union, 2022. [2022-10-17]. https://www.consilium.europa.eu/en/policies/sanctions/restrictive-measures-against-russia-over-ukraine/sanctions-against-russia-explained/.

[4] WEALTH-X. Oil Rises Above $100 A Barrel for The First Time Since 2014 [EB/OL]. Wealth-x, 2022-02-24. [2022-10-17]. https://www.wealthx.com/intelligence-centre/daily-news/2022/oil-rises-above-100-a-barrel-for-the-first-time-since-2014/.

[5] BUSINESS TODAY DESK. Ukraine receives around $100 MN in crypto donations [EB/OL]. Business Today, 2022-06-28. [2022-10-17]. https://www.businesstoday.in/crypto/story/ukraine-receives-around-100-mn-in-crypto-donations-325660-2022-03-11.

[6] COX C. Treasury warns against Russia's efforts to evade sanctions with cryptocurrencies [EB/OL]. CNBC, 2022-09-21. [2022-10-17]. https://www.cnbc.com/2022/09/20/treasury-department-russia-avoid-sanctions-using-crypto.html.

[7] Bouoiyour J, Mensi W, Selmi R, et al. Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold [J]. Refk Selmi.

[8] Chancharat S, Butda J. Return and volatility linkages between bitcoin, gold price, and oil price: Evidence from diagonal BEKK–GARCH model [M] // Environmental, social, and governance perspectives on economic development in Asia. Emerald Publishing Limited, 2021.

[9] Devarajan S, Mottaghi L. Middle East and North Africa Economic monitor, April 2017: The economics of post-conflict reconstruction in MENA [M]. World Bank, 2017.

[10] Iqbal N, Fareed Z, Wan G, et al. Asymmetric nexus between COVID-19 outbreak in the world and cryptocurrency market. 2021.

[11] INVESTING.COM. Stock market quotes & financial news [EB/OL]. Investing.com, [2022-9-25]. https://www.investing.com/.

[12] Greene W H. Econometric Analysis PDF eBook: Global Edition, 7/E.

[13] SINGH A. Multivariate time series: Vector auto regression (VAR) [EB/OL]. Analytics Vidhya, 2018-09-27. (2022-06-16) [2022-10-17]. https://www.analyticsvidhya.com/blog/2018/09/multivariate-time-series-guide-forecasting-modeling-python-codes/.

[14] KENTON W. Autoregressive conditional heteroskedasticity (ARCH) definition [EB/OL]. Investopedia, Investopedia, 2021-10-31. [2022-10-17]. https://www.investopedia.com/terms/a/autoregressive-conditional-heteroskedasticity.asp.

[15] Williams B. Betreuung: Prof. Dr. Rainer Dahlhaus [J]. 2011.

[16] Alloza M. A very short note on computing impulse response functions [J]. London: University College. Available online: http://www.ucl.ac.uk/~ {} uctp041/Teaching_files/Tutorial_IRF. pdf (accessed on 25 September 2020), 2017.

[17] PENN STATE EBERLY COLLEGE OF SCIENCE. 10.2 - autocorrelation and time series methods [EB/OL]. 10.2 - Autocorrelation and Time Series Methods | STAT 462, 2022. [2022-10-17]. https://online.stat.psu.edu/stat462/node/188/.