ATLANTIS PRESS

*Advances in Economics, Business and Management Research, volume 215*

**Proceedings of the 2022 7th International Conference on Social Sciences and Economic Development (ICSSED 2022)**

# How Does the COVID-19 Impact the Cryptocurrency?
## An empirical analysis using impulse response and ARMAX-GARCH

Junbo Huang[1, *]

[1] *The College of Wooster, United States of America*
**Email: jhuang21@wooster.edu*

**ABSTRACT**

This paper aims to investigate the interaction between the Covid-19 pandemic and the prices of two representative cryptocurrencies. We analyze the conditional variance of the log rate of return for these two cryptocurrencies using the ARMAX-GARCH model and the interaction between the pandemic severity and the log rate of returns using VAR-based impulse responses analysis. Our finding pointed out that the pandemic has a significant positive impact on the cryptocurrencies' prices in the short run, making the cryptocurrency market a good investment to hedge the pandemic-implanted risks in the conventional financial market.

***Keywords:*** *Covid-19, Cryptocurrency, Investment, Finance, Time-series analysis.*

## 1.INTRODUCTION

Since 2008, when Bitcoin was born, the cryptocurrency had become one essential element in the financial system, intending to create a decentralized monetary system. The initiation and recording of traditional money transfers relied on the banking systems in the past. Such extra effort will generate extra transaction costs and needlessly decrease the efficiency of the financial system. Moreover, after the gold standard is abolished, the value of the legal note in a country entirely depends on the government's credit. In some extreme circumstances, such as severe stagflation, an over-supply of money, or an economic recession, the government might lose its credit and its legal note to lose value.

In contrast, bitcoins significantly improve the situation we mentioned above. Since its "minable" quantity is within a limitation, people will not worry about the risk of depreciation of bitcoin's value. Also, with blockchain technology, the transaction can be recorded and initiated efficiently, automatically, and safely. These advantages soon make bitcoins become one of the fashionable topics around the globe. Since then, the market size of the cryptocurrency has proliferated – from only 1 type (the bitcoin) to over one thousand types. The creation of cryptocurrency provides people with a new convenient way of trading and transaction.

However, since cryptocurrency is a relatively new concept in the financial world, it attracts many investors to the hype and speculates its related market. These investment activities make cryptocurrency sometimes associated with high uncertainties and volatility in its value. After 2017, the value of bitcoin rises sharply from below 1000 dollars per bitcoin to over 10000 dollars per bitcoin. Since then, the value of bitcoins has begun to fluctuate between 4000 USD/bitcoin and 10000 USD/bitcoin.

In early 2020, the initiation of the covid-19 pandemic stakes the global economy harshly. Both the commodities market and the stock market are implicated severely. Due to the panic within both the financial and the industrial system, the US stock market had triggered the circuit breakers several times, and the WTI oil prices for May dropped to a negative number. These financial anomalies are infrequent. Several months later, with the normalization within the industries and the release of governmental market-stimulation packages, people's expectations of the economy are stabilized, and the money supply within the market flourished.

Consequently, the prices for all financial assets began to rise again and eventually have reached an extremely high point. The prices of cryptocurrencies, especially bitcoin, have overgrown to a high point of roughly 60000 USD/bitcoin and have been fluctuating harshly since early 2020. Researchers have investigated how different financial assets interact with the prices of cryptocurrencies, providing precious information for investors in making investment decisions. For example, by constructing an NLS and ARMA for the bitcoin prices, crude oil prices, and gold price, Renad Frehat et al. found that the covid-19 pandemic positively impacted gold prices and negatively impacted the crude oil prices. He also found that the death rate negatively impacted the bitcoins prices, and the newly confirmed positively impacted the prices [1].

Such abnormality has also attracted many scholars to study the pandemic impacts on all kinds of cryptocurrencies. These scholars pointed out that the pandemic profoundly impacted the cryptocurrency market's characteristics and trends in various ways. For instance, Ahmet Faruk Aysan et al. discovered that the pandemic changed the inter-relationship among three top cryptocurrencies (bitcoin, Binance, and Ripple) by applying a cointegration test and constructing a VEC model [2]. Šarūnas Galgauskas, in his master thesis, pointed out that there is an abnormally high variance in the prices of Bitcoin, Ethereum, and Ripple in a change point date around the mid-March of 2020 by applying change point detection techniques, such as PELT, BinSeg, and AMOC [3]. Beum-Jo Park demonstrated that the declaration date of covid-19 has a structural break in the bitcoin features market, and the ongoing pandemic prominently increases the market concerns for the future economic risk [4]. Khanh Quoc Nguyen explains how the stock market has a spillover effect on the bitcoin market, and the stock market is more correlated to the cryptocurrency market during the pandemic time by performing a VAR-GARCH analysis [5].

Many researchers also found that cryptocurrency can be used to hedge the risk created by the pandemic, and therefore it is valuable for investors to add cryptocurrencies into their portfolios. For instance, Ender Demir et al. stated that the cryptocurrency could be used as a hedging asset during the pandemic by showing a causal relationship between the covid-19 and the prices of cryptocurrencies by applying a wavelet coherence analysis [6].

More interestingly, since the lockdowns severely reduced mobility, and most of the entertainment was banned during the pandemic, many ordinary people began to engage more in personal investment activities according to the increase in the financial asset prices. Alexander Guzmán et al. pointed out that the bitcoin market has become a substitution for gambling activities and a way of entertainment for people since the pandemic started. Alexander Guzmán et al. also stated that such crowding in the cryptocurrency market inevitably created a bubble [7].

In this paper, we will investigate the impact of the pandemic on cryptocurrency by constructing ARMA-GARCH models to analyze the relationship between the progress of the covid-19 and the price changes of 2 representative cryptocurrencies, while also using VAR models and impulse response analysis to investigate the short-run disturbance between the pandemic and those cryptocurrencies' prices. Finally, it is conducive to detect and analyze such impacts because this beneficial information might assist investors in making investment decision (especially hedging) and the regulators in financial policymaking.

## 2.METHODS

To analyze our main research question regarding the relationship between the pandemic newly confirmed, which are addressed in China, the US, and the World, and two of the well-known cryptocurrencies price over time, which are the Bitcoin and the ETH, we established both VAR-based impulse response analysis and ARMAX-GARCH.

In 1969, the paper "Investigating Causal Relations by Econometric Models and Cross-spectral Methods" by W. J. Granger investigated how cross-spectral methods can be applied within the research in economics and figured out a way to clarify the causality and feedback between time series mathematically. He defined that if two or multiple time series X (x1 x2 x3…) are stationary and contain information in the past that help predict some other time series Y (y1 y2 y3) and if the information is not contained in the time series other than the predictors we used, then we can say the predictors X granger cause Y [8].

However, these methods are later mentioned by Granger and other econometrics and statistician as that the causality is atheoretical, meaning that the existence of a statistically significant result in the Granger causality test does not prove the existence of actual practical causality. Therefore, Granger causality must be highly associated with a typical theory development process to prove its usefulness.

However, not until Christopher Sims began to apply the vector autoregression model in the macroeconomics field in the 1970s, vector autoregression, or VAR, people were not provided with a helpful tool to analyze the causal relationship between two or more time series. The use of VAR in predicting a critical economic parameter in the future by analyzing the history of some other critical economic parameters possible. Within the model, we built equation systems for two or multiple time series, take their current data as multiple response variables, and the lagged data of all the corresponding time series for each multiple response variable. This process can be denoted as the following equation, where "m" is the lagged number and "n" is the variables included within the systems:

$$y_1 = \beta_{10} + \beta_{11} * y_{1t-m} \dots + \beta_{1m} y_{2t-m} + \epsilon_1 \quad (1)$$

$$y_2 = \beta_{20} + \beta_{21} * y_{2t-m} \dots + \beta_{2m} y_{1t-m} + \epsilon_2 \quad (2)$$

…

$$y_n = \beta_{n0} + \beta_{n1} * y_{nt-m} \dots + \beta_{nm} y_{nt-m} + \epsilon_n \quad (3)$$

This system could also be denoted in the form of matrixes. For example, a bivariate VAR system can be denoted as the following [9]:

$$\mathbf{Y} = \mathbf{A} + \mathbf{B_1}\mathbf{Y_{t-1}} + \cdots + \mathbf{B}_m\mathbf{Y_{t-m}} + \mathbf{E} \quad (4)$$

$$\mathbf{Y} = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}, \mathbf{A} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix}, \mathbf{B_1} \begin{pmatrix} \beta_{11} & \gamma_{12} \\ \beta_{21} & \gamma_{22} \end{pmatrix}, \ \mathbf{E} = \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix}$$

$$\mathbf{B}_m = \begin{pmatrix} \beta_{1m} & \gamma_{1m} \\ \beta_{2m} & \gamma_{2m} \end{pmatrix} \ \mathbf{Y_{t-1}} = \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} \ \mathbf{Y_{t-m}} = \begin{pmatrix} y_{1,t-m} \\ y_{2,t-m} \end{pmatrix}$$

Here, $m$ is denoted as the number of lags term included within each linear relationship. $\mathbf{Y}$ is an $2*1$ matrix that represents the response variables in each linear relationship, $\mathbf{A}$ is an $2*1$ matrix that represents the constants in each linear relationship. $\mathbf{B_1}$ and $\mathbf{B_m}$ are $2*m$ matrixes that contain all the coefficients for each lag term of each explanatory variables in each linear relationship. $\mathbf{Y_{t-1}}$ and $\mathbf{Y_{t-m}}$ are $2*1$ matrixes that contain all observed values for the explanatory variables, and $\mathbf{E}$ is an $2*1$ matrix that contains the error terms for each regressed linear relationship.

By running OLS and estimating the coefficient and constant term for each equation within the constructed system, we can analyze the Granger causality, perform an impulse test which tells the direction and magnitude of a unit impact of an impulse variable on response variables, and perform a variance decomposition to seek for the percentage of the impact of one variable among all impact. One thing noteworthy is that Sims, in his later 1980 paper, again re-identified some deviation of the economic modeling and the reality. He states that even when the explanatory variables, in a statistical model, well explain the response variables, the model itself does not invoke economic theory but only intuition [10].

In his paper in 1987, Engle introduced the ARCH model and showed three examples in economic studies [11]. The change in time-series volatility over time has created obstacles for economic researchers to analyze the interaction between variables. The ARCH model allows researchers to analyze time series with conditional variance over time. The model contains two-equation – a mean equation and a variance equation. The equations are mathematically addressed below:

$$Conditional\ mean:\ y_t = X_t\beta_t + \epsilon_t \quad (5)$$

$$Conditional\ variance:\ \sigma_t^2 = \gamma_0 + \sum_{i=1}^{i}\gamma_i\epsilon_{t-i}^2 \quad (6)$$

Following Engle's introduction, the $\sigma_t^2$ is the square of the error term at the current lag. Such error term for the mean equation follows a Gaussian distribution. However, such specification of the model is flexible. The distribution of the error term could be addressed in other common distributions, especially for financial economists, who usually need to deal with the non-normally-distributed return rates. By estimating the coefficients for both equations simultaneously with MLE, the model could then account for the conditional variance – usually presented as abnormal bursts in the original series.

This paper aimed to create two analyses – one for Bitcoin and the other for ETH, each analysis containing modeling between the daily close price and the pandemic newly confirmed data taken from the US, China, and the World. Each analysis contains three bivariate VAR models and 5 ARMAX-GARCH models. The models are mathematically specified in the below equations:

Bivariate VAR model:

$$\begin{pmatrix} Price_1 \\ Pandemic_2 \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}\begin{pmatrix} Pandemic_{t-1} \\ Price_{t-2} \end{pmatrix} + \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} \quad (7)$$

ARMAX-GARCH model:

$$Conditional\ mean:\ Price = Pandemic_t\beta_t + \epsilon_t \quad (8)$$

$$Conditional\ variance:\ \sigma_t^2 = \gamma_0 + \sum_{i=1}^{i}\gamma_i\epsilon_{t-i}^2 \quad (9)$$

The price data for the two cryptocurrencies were taken from Yahoo Finance, and the prices are denoted as daily closing prices in the unit of dollars. Then, we took the log rate of return for both cryptocurrencies and used those log rates of return as our response variables for modeling. Our pandemic data was taken from ourworldindata.org, a public database run by the University of Oxford and other famous patrons. The pandemic newly confirmed was also transformed into the logarithmic form. The time range of the data was from January 23rd, 2020, to November 5th, 2021, giving a total of 653 observations.

We tested the stationarity for all series using the ADF test. The result showed that all series we used here is stationary at level I(0). The test results are presented in Table 1.

**Table 1.** ADF test result

| Variable name | Variable explanation | ADF test statistics | Stationarity |
|---|---|---|---|
| ln_new_china | China 's Newly confirmed | -7.379 (p-value:0.0000) | I(0) |
| ln_new_us | US 's Newly confirmed | -3.679 (p-value:0.0044) | I(0) |
| ln_new_world | World 's Newly confirmed | -4.935 (p-value:0.0000) | I(0) |
| bit_lnrate | Bitcoin's log rate of ruturn | -27.955 (p-value:0.0000) | I(0) |
| eth_lnrate | ETH's log rate of ruturn | -28.197 (p-value:0.0000) | I(0) |

## 3.RESULTS

In this section, we had constructed and examined the results from the VAR and the ARMAX-GARCH models using the series we addressed above. We first began with the VAR and impulse response analysis for the bitcoin price. We chose our best lag numbers for all three models based on the information criteria, such as AIC and HQIC computed by STATA.

However, after several trials with optimal lags, we consistently saw the serial correlation within all models except with only China's newly confirmed series. China's extraordinary phenomenon might result from China's short, intense pandemic period and low volatility in the newly confirmed data. Hence, we also determined our optimal number of lags by taking account of the severity of serial correlation. Eventually, we decided to use 12 lags for the US newly confirmed model, four lags for the China newly confirmed model, and 11 lags for the World newly confirmed model. All three VAR models were stable, but only the China model was entirely free from the serial correlation problem. Figure 1-3 are the response analysis for Bitcoin.

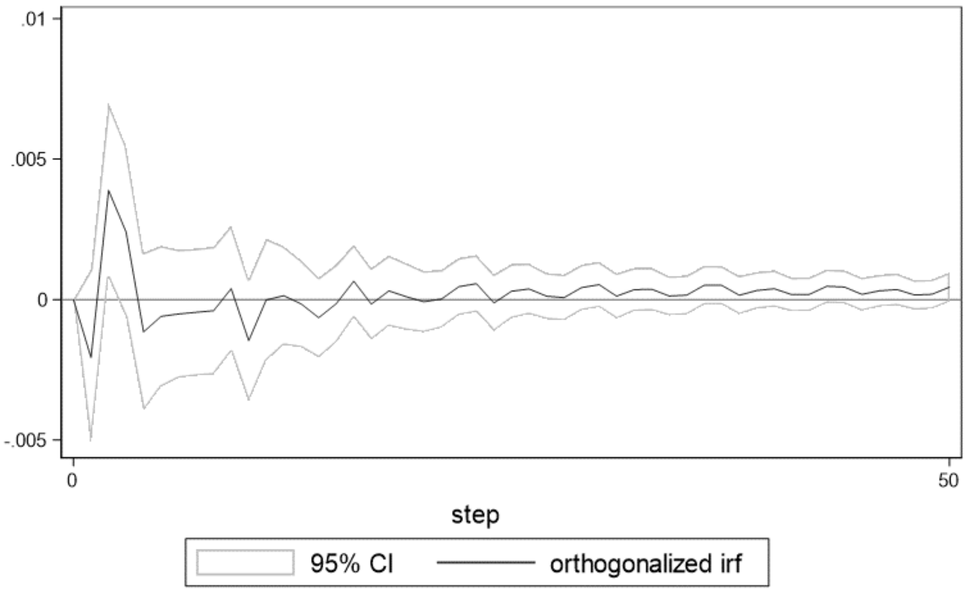


**Figure 1.** The impulse response from the log of the US' newly confirmed on bitcoin's log rate of return

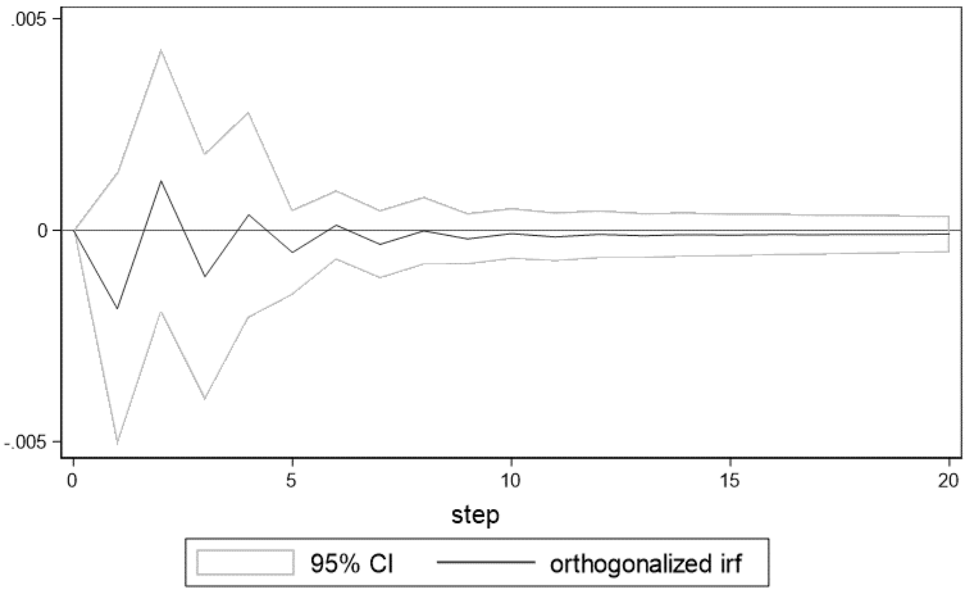


**Figure 2.** The impulse response from the log of China's newly confirmed on bitcoin's log rate of return

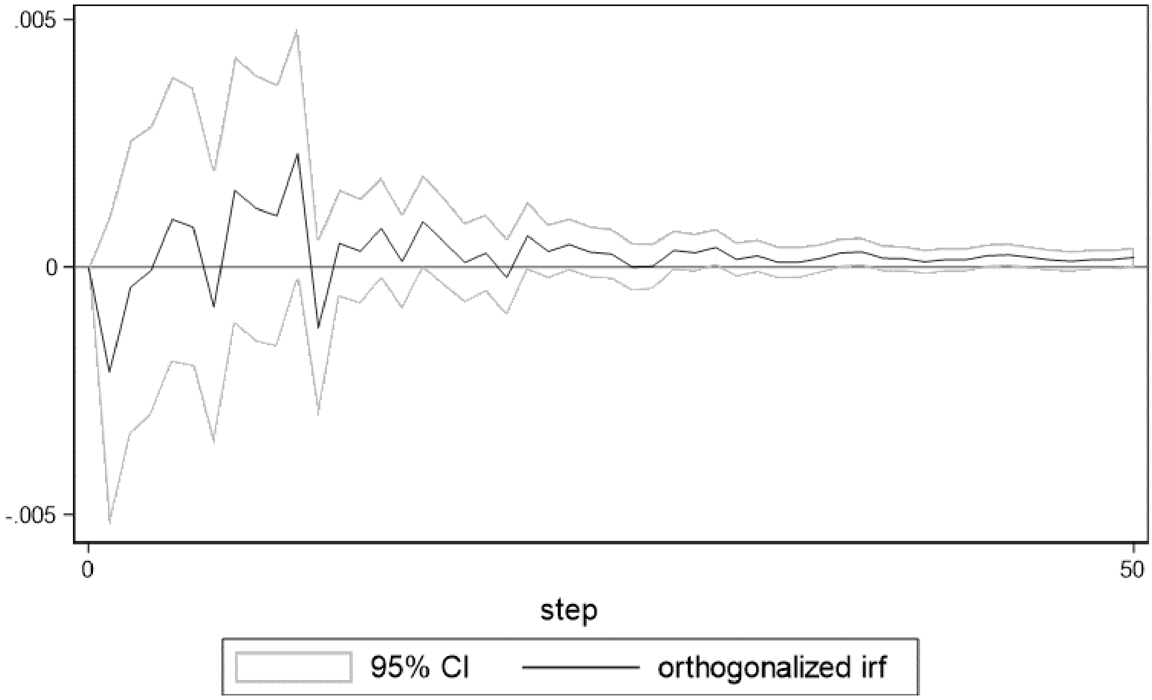


**Figure 3.** The impulse response from the log of the World's newly confirmed on bitcoin's log rate of return

In the US-bitcoin model, from the Wald-test, we found a bidirectional Granger causality between the log of newly confirmed and the bitcoin's log return rate. Also, under this 12-lag bivariate VAR system, one standard deviation of shocks in the error term of logarithmic US newly confirmed will approximately have a 10-lag period of impact on the bitcoin's log rate of return. Noteworthily, such impact is expected to be significantly positive during the 2nd lag under the 95% confidence level (the third lag is also significant if we extend the CL to 90%). This substantial magnitude of positive impulse implies that an increase in the Covid-19 newly confirmed in the US might result in a rise in the return rate roughly 2 to 3 days later.

In the China-bitcoin model, we found that, under this 4-lag bivariate VAR system, one standard deviation of shocks in the error term of logarithmic US newly confirmed will approximately have a 5-lag period of impact on the bitcoin's log rate of return. Compared to the result from the US model, the direction of impacts of China's newly confirmed seems to be more ambiguous since the impulse is oscillating around 0.

Nevertheless, it is vital to clarify that the pandemic condition in China is far different from the conditions in all other countries in the World. For example, when the pandemic was eroding China, the pandemic was still not as influential as it would be later, and now we can hardly see newly confirmed in China, and its pandemic development is independent of the World's development. Such behavior is evident in the result of the Granger causality test – there is no Granger causality between the two series.

We also observed no Granger causality between the two included series in the world-bitcoin model. Nonetheless, the impulse response was similar to that of the US model. The impact duration is around 10 lags, and the direction of the impact is negative at first and positive after the 3rd lag. However, such impulse response is not statistically significant under 95% CL.

Also, we constructed the models for the ETH in a similar pattern as well. The optimal lags we found for the US, China, and world models are also 12, 4, and 11. One more consideration in choosing lags here was that we tried to match the chosen lag number with the bitcoin analysis while maintaining safe conditions for the models. Expectedly, we could better compare the two analyses and generate a better holistic picture for the whole cryptocurrency market. Figure 4-6 are the impulse response analysis for ETH's log rate of return:

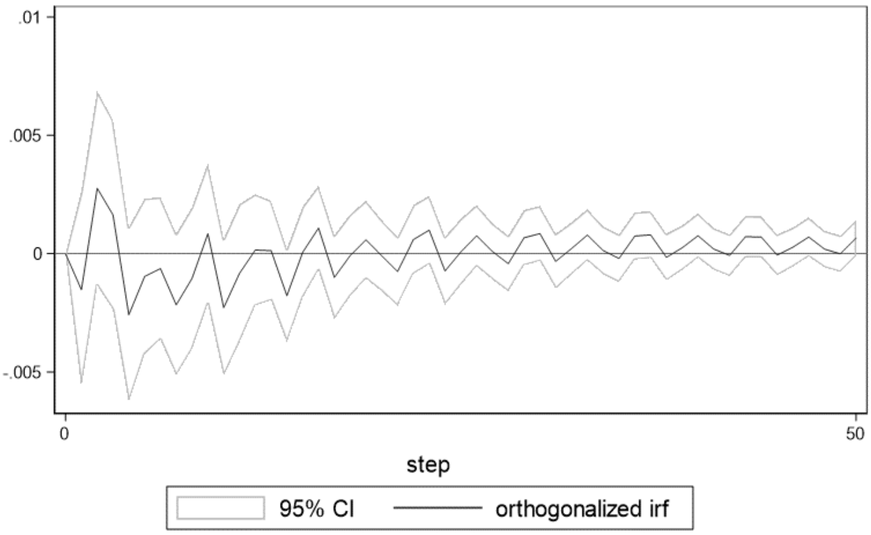


**Figure 4.** The impulse response from the log of US' newly confirmed on ETF log rate of return

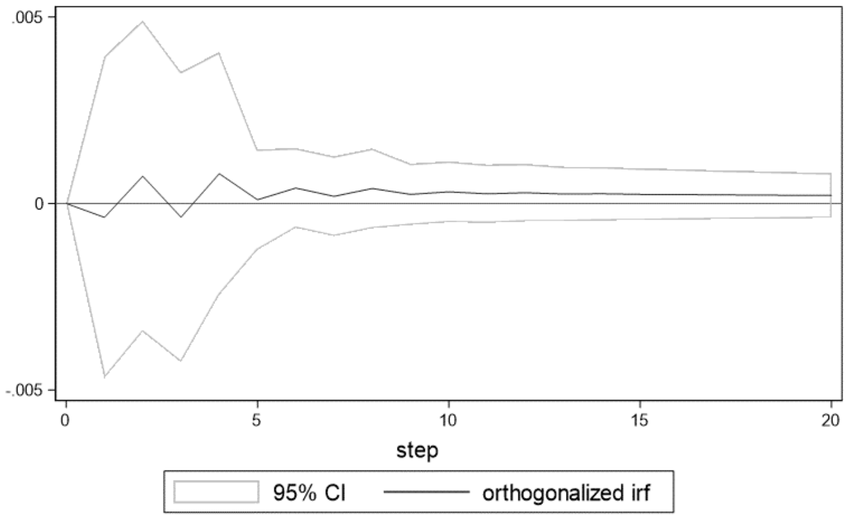


**Figure 5.** The impulse response from the log of China's newly confirmed on ETF log rate of return

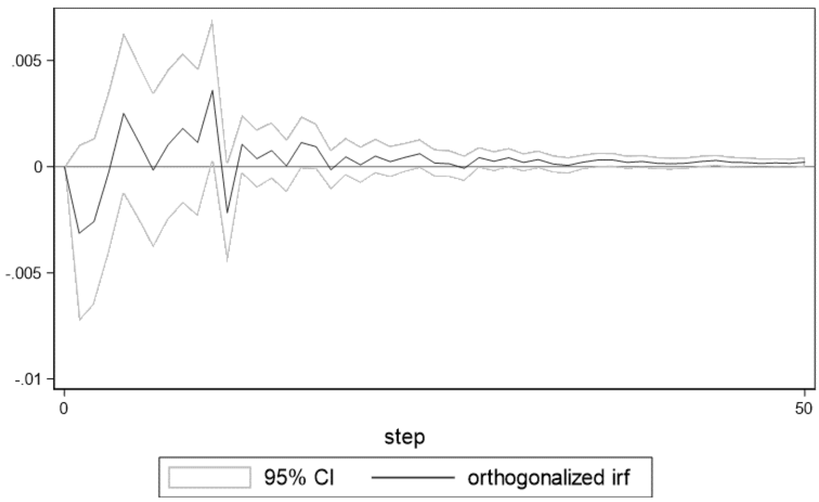


**Figure 6.** The impulse response from the log of World's newly confirmed on ETF log rate of return

The impulse response of the US-ETH model showed a dissimilar pandemic-return relationship with the bitcoin. For ETH, the direction of the impulse from log US newly confirmed on ETH's log rate of return is more ambiguous. Such impulse converges at a much slower speed than the impulse in the US-bitcoin models. However, the impulse response patterns from the China-ETF and the World-ETF models aligned with the patterns in the bitcoin analysis, indicating there is still some similarity between the bitcoin and the ETF. The 10th-lagged impulse of the World newly confirmed is statistically significantly positive, indicating that the world pandemic conditions also significantly positively impact the ETH return rate.

After the impulse response analysis, we started to construct the ARMAX-GARCH model. We first graphed the autocorrelation and partial autocorrelation graph to determine the suitability of the ARMAX equations. We found that, for both ETF and bitcoin, there were significant AC and PAC terms with lags 1 and 4. Combining the information criteria, we decided to use ARMAX(1,1) with no differentiation as our mean equation for the GARCH analysis. Adding the mainstream GARCH(1,1) specification, we then yielded the final model – the ARMAX(1,1)-GARCH(1,1) model.

Table 2 is the result for all bitcoin models (noticing that the estimated coefficients for the ARMAX process are not presented in the table since they are not this paper's primary focus).

**Table 2.** ARMAX-GARCH for BIT, variance equation

| Variables | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Rate of return, ETH | | | | |
| | | | Newly Confirmed Cases | | |
| China (-1) | 0.0016 | | | 0.0011 | 0.0023* |
| | (0.0011) | | | (0.0014) | (0.0013) |
| US (-1) | | -0.0009** | | -0.0005 | 0.0038*** |
| | | (0.0005) | | (0.0006) | (0.0014) |
| The World (-1) | | | -0.0029*** | | -0.0078*** |
| | | | (0.0008) | | (0.0021) |
| | | | ARCH | | |
| ARCH(-1) | 0.1212*** | 0.1175*** | 0.1148*** | 0.1210*** | 0.1241*** |
| | (0.0232) | (0.0245) | (0.0229) | (0.0257) | (0.0240) |
| GARCH(-1) | 0.8580*** | 0.8651*** | 0.8708*** | 0.8627*** | 0.8614*** |
| | (0.0245) | (0.0233) | (0.0212) | (0.0242) | (0.0223) |
| Constant | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |

The result indicates that the ARCH effect is present in all 5 models, which have different specifications – all ARCH and GARCH terms are statistically significant under the 1% confidence level. The coefficient for the log China's newly confirmed in the China-Bitcoin GARCH model is not statistically significant, implying that the relationship between China's pandemic condition and the Bitcoin return rate is weak. In contrast, the coefficients for both the log US newly confirmed and the log world newly confirmed are significant under 95% confident level, implying the relationships between those two series and the bitcoin return rate are strong.

All coefficients in the China-US-World-Bitcoin model are significant under 1% confident level except for China's coefficient, which is significant at a 10% level, implying that the pandemic condition, specifically the newly confirmed cases, has profound short-run impacts on the log rate of return for Bitcoin. The weaker significance of China's coefficient pointed out that the market is impacted by the world pandemic condition or the US pandemic condition more. This finding matches the practical aspect – China is the least severe in its pandemic condition than everywhere else.

Table 3 is the ARMAX(1,1)-GARCH(1,1) model for ETH with the same specification:

**Table 3.** ARMAX-GARCH for ETH, variance equation

| Variables | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Rate of return, ETH | | | | |
| | | | Newly Confirmed Cases | | |
| China (-1) | 0.0032** | | | 0.0034* | 0.0038** |
| | (0.0013) | | | (0.0017) | (0.0018) |
| US (-1) | | -0.0011** | | 0.0001 | 0.0017 |
| | | (0.0005) | | (0.0007) | (0.0023) |
| The World (-1) | | | -0.0019* | | -0.0029 |
| | | | (0.0010) | | (0.0036) |
| | | | ARCH | | |
| ARCH(-1) | 0.1387*** | 0.1329*** | 0.1335*** | 0.1386*** | 0.1393*** |
| | (0.0168) | (0.0166) | (0.0170) | (0.0179) | (0.0184) |
| GARCH(-1) | 0.8546*** | 0.8587*** | 0.8570*** | 0.8543*** | 0.8531*** |
| | (0.0185) | (0.0177) | (0.0181) | (0.0187) | (0.0193) |
| Constant | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** |
| | (0.0000) | (0.0000) | (0.000) | (0.0000) | (0.0000) |

The result shows a different picture from the one of Bitcoin, except that both analyses contain significant ARCH effects. Although ETH price is significantly related to all newly confirmed series from each area, such relation no longer holds when adding multiple newly confirmed series into the model. Compared to China's coefficients in the Bitcoin models, China's coefficients in the ETH model set are more statistically significant in both the full and bivariate models. This phenomenon indicates that the behavior of the ETH is different from that of Bitcoin, implying that different cryptocurrencies might have different pandemic-implanted characteristics.

## 4.DISCUSSION

In general, our findings did not oppose other researchers' findings. The pandemic development profoundly impacts the cryptocurrencies market. From the VAR-based impulse response analyses for the two cryptocurrencies and the significant GARCH terms in the ARMAX-GARCH model, we saw that, in the short term, a severer pandemic condition would arouse hotness in the cryptocurrency market.

This phenomenon might be a consequence of different reasons. First, in the long run, a severer pandemic development requires the public sector to release a much looser monetary policy, providing more extra funds for the private sector to speculate and invest in the cryptocurrency market. Second, because cryptocurrencies are always a good investment for people over time, it is not strange to see an increase in hotness in the cryptocurrency market. Third, since the prices for cryptocurrencies have been volatile in recent years, the loosened monetary policy and the embedded high volatility characteristic push the price up.

Also, we saw that the pandemic impacts on the ETH and Bitcoin are not entirely identical. One explanation might be that Bitcoin is more famous and is speculated by more well-known people, such as Elon Musk. The media manipulation by these influential investors increases the wish for people to invest in these top cryptocurrencies, consequently pushing these top cryptocurrencies' prices higher.

## 5.CONCLUSION

This paper aims to discover how the severity of the Covid-19 and the prices of several major cryptocurrencies interact. By building VAR-based impulse response analysis and ARMAX-GARCH model, with the Bitcoin price and the ETH price data taken from Yahoo finance and the pandemic newly confirmed data taken from an Oxford-University-operated public database, we found that the development of the pandemic has a significant positive short-run impact on the log rates of return of the cryptocurrencies. Although the pandemic development was found to have different magnitudes of impact on different cryptocurrencies, the directions of such impacts do not vary.

Therefore, we suggest that investors utilize the positive correlation between the returns of cryptocurrencies and the pandemic development to hedge the potential pandemic-introduced risks in the conventional stock and commodity market.

## REFERENCES

[1] Frehat, Renad, et al. “The Third Refereed Conference of the Faculty of Economics and Social Sciences ‘The Challenges of the Palestinian Economy in the Face of Political Pressure andthe Repercussions of the Corona Crisis.’” النجاح جامعة الوطنية, The Impact of COVID-19 Pandemic on Safe Havens: Bitcoin Currency, Crude Oil and Gold Prices, 2021, https://staff.najah.edu/en/publications/12172/. Accessed 2021.

[2] Aysan, Ahmet Faruk, et al. “Bitcoin and Altcoins Price Dependency: Resilience and Portfolio Allocation in Covid-19 Outbreak.” Risks, vol. 9, no. 4, 2021, p. 74., https://doi.org/10.3390/risks9040074.

[3] Galgauskas, Šarūnas.“Modelling the Dynamics of Bitcoin, Ethereum, Ripple Including Covid 19 Impact.” VILNIUS UNIVERSITY, 2021.

[4] Park, Beum-Jo. “The COVID-19 Pandemic, Volatility, and Trading Behavior in the Bitcoin Futures Market.” Research in International Business and Finance, vol. 59, 2022, p. 101519., https://doi.org/10.1016/j.ribaf.2021.101519.

[5] Nguyen, Khanh Quoc. “The Correlation between the Stock Market and Bitcoin during COVID19 and Other Uncertainty Periods.” Finance Research Letters, 2021, p. 102284., https://doi.org/10.1016/j.frl.2021.102284.

[6] Demir, Ender, et al. “The Relationship between Cryptocurrencies and Covid-19 Pandemic.” SSRN Electronic Journal, 2020, https://doi.org/10.2139/ssrn.3585147.

[7] Guzmán, Alexander, et al. “Trading Cryptocurrencies as a Pandemic Pastime: Covid-19 Lockdowns and Bitcoin Volume.” Mathematics, vol. 9, no. 15, 2021, p. 1771., https://doi.org/10.3390/math9151771.

[8] Granger, C. W. (1969). Investigating causal relations by econometric models and cross spectral methods. Econometrica, 37(3), 424. https://doi.org/10.2307/1912791

[9] Chen, Qiang. “20.9 Vector Autoregressive Processes.” Advanced Econometrics and Stata Applications (Second Edition), Higher Education Press, 2014, pp. 375－377.

[10] Sims, C. A. (1980). Macroeconomics and reality. Econometrica, 48(1), 1. https://doi.org/10.2307/1912017

[11] Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating time varying risk premiain the term structure: The ARCH-M model. Econometrica, 55(2), 391. https://doi.org/10.2307/1913242