The COVID-19 and Dynamics in Cryptocurrencies: An empirical evidence

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Abstract. The coronavirus pandemic occurred in 2019 and caused an impact on cryptocurrencies. This paper focuses on the relation between the return of cryptocurrencies and the new daily confirmed cases of COVID-19 worldwide, taking Bitcoin, Ethereum, and Tether as three examples. It is shown that the new daily cases have a significant influence on Bitcoin and Ethereum. And the short-term impact of new global confirmed cases on Bitcoin is positive, then remains volatile and eventually disappears. The different phenomena show that different cryptocurrencies have reacted differently to the pandemic impact.

Keywords: COVID-19; Cryptocurrencies; Volatility; Empirical research

1. Introduction

Coronavirus disease 2019 (COVID-19) is an infectious disease caused by Severe Acute Respiratory Syndrome Coronavirus type 2 (SARS-CoV-2). The infectious disease has triggered an ongoing global outbreak since its outbreak in late 2019. The coronavirus has now undergone multiple mutations and COVID-19 has now become one of the deadliest epidemics in human history. Due to the highly contagious and lethal nature of the coronavirus, people's lives and work are being affected to varying degrees. The need for home isolation has also caused a reduction in activities outside the home, a drop in consumption, cold winter in the real economy, and even a downward spiral in the global economy. Consumers' economic behavior and investment choices have been affected as a result. However electronic cryptocurrencies are showing a very different trend from traditional commodities under the impact of the COVID-19. As a medium of exchange that uses cryptographic principles to secure transactions and control the creation of transaction units, electronic currencies are based on their decentralized consensus mechanism, as opposed to banking and financial systems that rely on a centralized regulatory system.

To explore the impact of COVID-19 on electronic cryptocurrencies, this paper attempts to summarize and sort out the main empirical studies and theoretical literature in the field of the economic environment and electronic cryptocurrencies in the context of the COVID-19. In the established literature, recent research showed that the strongest structural breaks in market prices occurred during the COVID-19 period by using a relatively new statistical method to analyze the time series of US market prices [1]. Further research has examined the financial contagion from the US, Japanese and Chinese markets to Asian markets during the Global Financial Crisis (GFC) and the COVID-19 pandemic crisis. The Digital Command Control (DCC) model is applied to examine volatility and conditional correlation between emerging financial markets during the GFC and the COVID-19 pandemic. [2] This literature focuses on the financial markets in the context of COVID-19. However, these aggregates tend to treat COVID-19 only as a given and do not specifically analyze the impact of COVID-19 on specific financial products and the economic environment.

In the established literature on electronic cryptocurrencies, the existing research showed the market value of two major cryptocurrencies, Ethereum and bitcoin, for the period 2017-to 2020 [3]. Further research has proved that the model uses a recurrent neural network (RNN) based on a long short-term memory (LSTM) approach algorithm to predict the price of cryptocurrencies and demonstrates the superiority of the method [4]. Both pieces of literature focus on cryptocurrency price
forecasting. Earlier in the literature, it has examined the different attitudes and policies of various countries toward cryptocurrencies [5]. According to the theory presented by Cong Gu et al. in 2021, the research showed the significant excess returns in the cryptocurrency market since the Federal Reserve initiated unlimited quantitative easing in March 2020 [6]. The analysis focuses on the impact of the policy on cryptocurrencies and the digital RMB. The literature covers the impact of other factors on cryptocurrencies but does not take the impact of COVID-19 into account.

The existing works of literature are talking about the macroscopical relation between cryptocurrency and the COVID-19. Specifically speaking, recent research shows that the self-shock effect of the COVID-19 has strong fluctuation and the fluctuation of in digital currency market has an obvious phase effect, which is a different fluctuation in performance [7]. Besides, the effect of COVID-19 on cryptocurrency in China and overseas is different – the correlation between China and the price index of the digital currency is negative but it is positive overseas. Further research compares the economic phenomenon in cryptocurrencies with those in major stock indices and finds that cryptocurrencies are more vulnerable during the COVID-19 period [8]. The theory presented by Muhammad Abubakr Naem in 2020, uses the asymmetric multifractal detrended fluctuation analysis (MF-DFA) to test the asymmetric efficiency of four specific cryptocurrencies - Bitcoin, Ethereum, Litecoin, and Ripple [9]. And the result shows that COVID-19 give an inefficient influence on cryptocurrencies and Bitcoin and Ethereum have the most impact during the time of the COVID-19.

In conclusion, the efficiency in the digital market changes in different periods, and the new disasters cause the inefficiency in cryptocurrencies. Recent research also showed that cryptocurrencies as a hedge against COVID-19. However, it finds that although COVID-19 has a negative impact in the first several years, it begins to change into positive relation in the later time, which proves that the cryptocurrency is a hedge [10]. Further research chooses the specific cryptocurrency – Bitcoin and analyses the relation between this cryptocurrency and the COVID-19. And the report shows that the outbreak of the COVID-19 makes the price of Bitcoin rise by using the wavelet method [11].

Based on the pieces of literature, it is a lack of investment in the long period of the COVID-19 pandemic and the specific cryptocurrencies from a microcosmic perspective. And most kinds of literature just focus on the current data and don’t make any predictions. Under this circumstance, firstly, this paper will be based on the background of the global epidemic since the outbreak of COVID-19 up to the Russian-Ukrainian conflict. And this paper will choose three electronic cryptocurrencies - Bitcoin, Ether, and USDT as examples and examine the impact of the new coronavirus epidemic, by using financial models such as ARMAX. Secondly, this paper will focus on the relation between the world’s daily confirmed cases of COVID-19 pandemic and the daily price in these three cryptocurrencies and use the time series model to evaluate these two factors in quantitative methods. Thirdly, this paper will predict future price movements in cryptocurrencies and give some suggestions on how to invest in cryptocurrencies with more rewards.

The following parts of the paper are organized as follows: Section 2 presents the research design, including data sources and model specification; Section 3 contains the empirical results and analysis based on the ARMAX, impulse response, and GARCH models; Section 4 is the discussion of the impact of the COVID-19 shock on electronic cryptocurrencies; Section 5 is the conclusion.

2. Research design

2.1 Data source

The data in this article includes the prices of Bitcoin, Ethereum, and Tether, as well as the number of new daily confirmed cases of the COVID-19 worldwide. The data is dated from the time of the COVID-19 outbreak to the time of the Russian-Ukrainian conflict in 2022. Specifically, data from January 24, 2020, to February 23, 2022, was chosen for analysis in this paper. Data on the global daily number of confirmed new cases of the COVID-19 in this paper is derived from the China Securities Market and Accounting Research (CSMAR). The CSMAR Databases offer data on the China stock markets and the financial statements of China’s listed companies. Data on the prices of
bitcoin, Ethereum, and tether in this paper is derived from Investing.com. It is the third-largest financial website in the world, providing real-time quotes on over 300,000 financial instruments from over 100 exchanges worldwide.

2.2 Unit root test

In this part, this paper uses the ADF test to check the existence of unit root to determine the stationarity of the data. The three confidence levels of this test are 1%, 5%, and 10%. First, this paper examines the stationarity of the Bitcoin, Ethereum, and Tether price series. As a result of the ADF test, the unit-roots of the price series of Bitcoin and Ethereum exist and the price series are not stationary, while the unit root of Tether does not exist, and its price series is completely stationary. Then, this part tests the stationarity of the return series of three electronic cryptocurrencies. The ADF test results show that the unit root of these three electronic cryptocurrencies' rate of return series does not exist. So, there is no existence of unit root, and their rate of return series is completely stationary. In the end, this part tests the global daily number of new confirmed cases (logarithm) and the stationarity of their difference series. The unit root of this series is also non-existent, which means that the logarithmic series of the global daily number of new confirmed cases is also stationary.

| Table 1. ADF-test |
|-------------------|-----------------|-----------------|
| Variable          | t-value         | p-value         |
| Price             |                 |                 |
| Bitcoin           | -1.2630         | 0.8968          |
| Ethereum          | -1.9860         | 0.6089          |
| Tether            | -8.3110         | 0.0000 ***      |
| Rate of return    |                 |                 |
| Bitcoin           | -19.6380        | 0.0000 ***      |
| Ethereum          | -19.3610        | 0.0000 ***      |
| Tether            | -27.0570        | 0.0000 ***      |
| COVID-19          |                 |                 |
| Ln newly confirmed cases | -4.0110 | 0.0085 *** |

2.3 Specification of ARMAX model

In this paper, the ARMAX model is used to analyze the relationship between the return rate of cryptocurrency and new daily confirmed cases worldwide. In other words, this paper adds other explaining variables into the ARMA model, using the past implementation values and past residuals to predict the future value and considering the contribution of other explaining variables. The ARMAX model is generally expressed as follows. $y_t$ is the explained variables and the explaining variables are its lagging term, the lag of the residual, and the lagging terms of other explanatory variables.

$$
y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + a_t + \sum_{i=1}^{q} \theta_i a_{t-i} + y_{11} x_{1,t-1} + \cdots + y_{1q_1} x_{1,t-q_1} + y_{k1} x_{k,t-1} + \cdots + y_{k q_k} x_{k,t-q_k}
$$

In this part, this paper will set six ARMAX models. In the ARMAX model, this paper uses the return of the cryptocurrency as the dependent variable. And $X$ is the logarithmic number of new daily confirmed cases. In some models, this paper will add the lag of the logarithmic number of new daily confirmed cases. Besides, this paper uses the plot of PACF and ACF to confirm the lag phase suitable for this model.
In the first ARMAX model, the dependent variable is the return of the Bitcoin. And according to figure 1, the lag in one phase of Bitcoin’s return has a strong correlation with the return itself. Therefore, AR (1) is used in the ARMAX model about the return of the Bitcoin. And this paper uses the lag one phase of residual because its number of the correlation is high in the ACF graph. In conclusion, ARMA (1,1) is modeled. And then the logarithmic number of new daily confirmed cases is added as X. So, the first ARMAX is set. And in the second model, there are two dependent variables, which means based on the first model, this paper adds the lag one phase of the logarithmic number for new daily confirmed cases. Then the second ARMAX model is finished.

![Figure 1. Identification for ARMA, bitcoin](image1)

The PACF and ACF graphs of Ethereum’s return also show that the lag in one phase of the return and the residual have a strong correlation with the return. So ARMA (1,1) is still used in the ARMAX model about Ethereum and Tether.

![Figure 2. Identification for ARMA, Ethereum](image2)

And from figure 3, the lag one phase of both the return and the residual has a strong correlation with the return itself. Therefore, the ARMA (1,1) model is still suitable for Tether.
2.4 Specification of VAR models

VAR model is used when being Concerned with the forecast of several economic variables. And in this model, all the variables are put together and predicted as a system. Under this circumstance, the predictions are mutually consistent. Assuming there are 2 time-series variables, the general VAR model is expressed as follows. \( y_1 \) and \( y_2 \) are these 2 time-series variables regarding as the explained variables of the two regression equations respectively. The explaining variables are the P-order lag values of two variables.

\[
y_{1t} = \beta_{10} + \beta_{11}y_{1,t-1} + \cdots + \beta_{1p}y_{1,t-p} + y_{11}y_{2,t-1} + \cdots + y_{1p}y_{2,t-p} + \varepsilon_{1t} \tag{2}
\]

\[
y_{2t} = \beta_{20} + \beta_{21}y_{1,t-1} + \cdots + \beta_{2p}y_{1,t-p} + y_{21}y_{2,t-1} + \cdots + y_{2p}y_{2,t-p} + \varepsilon_{2t} \tag{3}
\]

The return of the cryptocurrency and the new daily confirmed cases have some relation to each other. And this paper wants to predict the variables in a long term precisely. Therefore, the VAR model is suitable for predicting the variables. To ensure the effectiveness of parameter estimation of the VAR model, the optimal lag order of the model is determined by using relevant information criteria. And according to the Final Prediction Error (FPE) and Akaike Information Criterion (AIC) criterion, this paper chooses the lag eleven phases to build the model of VAR (11).  

| Lag | FPE   | AIC     | HQIC    | SBIC    |
|-----|-------|---------|---------|---------|
| 1   | 8.1e-12 | -14.1867 | -14.1392 | -14.0634* |
| 2   | 7.6e-12 | -14.2572 | -14.1717* | -14.0353 |
| 3   | 7.4e-12 | -14.2728 | -14.1493 | -13.9522 |
| 4   | 7.6e-12 | -14.2578 | -14.0962 | -13.8384 |
| 5   | 7.6e-12 | -14.2550 | -14.0554 | -13.7370 |
| 6   | 7.5e-12 | -14.2684 | -14.0308 | -13.6518 |
| 7   | 7.5e-12 | -14.2596 | -13.9839 | -13.5443 |
| 8   | 7.5e-12 | -14.2672 | -13.9535 | -13.4532 |
| 9   | 7.4e-12 | -14.2810 | -13.9294 | -13.3684 |
| 10  | 6.6e-12 | -14.3915 | -14.0018 | -13.3802 |
| 11  | 6.3e-12* | -14.4392* | -14.0114 | -13.3292 |
| 12  | 6.4e-12 | -14.4209 | -13.9552 | -13.2123 |
From the test of Stata, the variables of this model have combined significance and the residual of the model is not autocorrelated. And VAR model is a stationary process because all the spots are inside the circle in figure 3. Therefore, the setting of VAR (11) is reasonable and effective.

![Figure 4. Stability of VAR system](image)

### 2.5 Specification of GRACH model

ARCH model is used for studying the regulation of volatility. And GRACH model reduces the number of parameters to be estimated and makes the prediction of future conditional variance much more precise. So, the GRACH model uses the conditional variance of the residual as the explained variables and the lag terms for both the conditional variances and residuals as the explaining variables. The general form of the GRACH model is shown below.

\[
\sigma^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \cdots + \alpha_q \varepsilon^2_{t-q} + \gamma_1 \sigma^2_{t-1} \\
+ \cdots + \gamma_p \sigma^2_{t-p}
\]  

In the model of GRACH, GARCH (1,1) is suitable for the data. This paper chooses the return of these three cryptocurrencies as the dependent variable and the logarithmic number of new daily confirmed cases as the exogenous variable in the first, third and fifth GRACH model. And in the second, fourth, and sixth CRACH model, the lag one phase for the logarithmic number of new daily confirmed cases is added as the second exogenous variable.

### 3. Empirical results and analysis

#### 3.1 Identification and result of ARMAX

According to Table 3, the lag one order of residual in the first and second models has a relatively remarkable negative effect on the return of Bitcoin. And the logarithmic number of new daily confirmed cases and the lag one phase have a strongly positive influence (P<0.01) on the return of Bitcoin in the second ARMAX model. So the numbers in the model have significant economic significance. It is represented by a 1% increase in the number of new global confirmed cases in the current period and a lag period, and the bitcoin yield will increase by 1.57% and 1.42% respectively. It explains that the COVID-19 pandemic has pushed up bitcoin prices to some extent. As for the return of Ethereum, both the logarithmic number of new daily confirmed cases and the lag one phase of it affect the return of Ethereum. The former is positive and the latter is negative. In other words, the COVID-19 also has a positive effect on the price of Ethereum, but it is more reflected in the volatility of the yield of Ethereum caused by the epidemic. The impact on Tether’s return doesn’t have economic significance because almost all the coefficients are zero.
Table 3. ARMAX model

| Variables | (1)     | (2)      | (3)     | (4)     | (5)     | (6)     |
|-----------|---------|----------|---------|---------|---------|---------|
| AR (-1)   | 0.0387  | 0.0401   | 0.0005  | 0.0118  | 0.4715*** | 0.4770*** |
|           | (0.1422)| (0.1358)| (0.1680)| (0.1580)| (0.0276)| (0.0270)|
| MA (-1)   | -0.3244** | -0.3303** | -0.2798 | -0.3015 | -0.8951*** | -0.9004*** |
|           | (0.1421)| (0.1355)| (0.1681)| (0.1577)| (0.0143)| (0.0137)|
| Ln newly confirmed cases | | | | | |
| T=0       | 0.0016  | 0.0157*** | 0.0018  | 0.0262*** | -6.57e-06 | -0.0000** |
|           | (0.0017)| (0.0027)| (0.0020)| (0.0029)| (3.39e-06)| (0.0000)|
| T=-1      | 0.0142*** | -0.0247*** | -0.0030 | -0.0000** | -0.0000** |
|           | (0.0031)| (0.0030)| (0.0030)| (0.0000)| (0.0000)|
| Constant  | -0.0181 | -0.0164 | -0.0190 | -0.0157 | 0.0001** | -0.0000** |
|           | (0.0209)| (0.0235)| (0.0250)| (0.0256)| (0.0000)| (0.0000)|

Note: The numbers in brackets are standard errors. The estimate is kept to 4 decimal places. Subsequent tables follow this rule.

3.2 Impulse response

In the early stage of the COVID-19 outbreaks, the increase of new daily confirmed cases causes the return of the Bitcoin to increase but the volatility of the Bitcoin’s return is reduced gradually and finally, it moves slightly around 0. And for the return of Ethereum and Tether, the increase of new daily confirmed cases lets it fluctuate in a certain range. At the end of the period, these return rates are also less volatile. In conclusion, the short-term impact of global new daily confirmed cases on Bitcoin is positive, then remains volatile and eventually disappears. The impact on Ethereum and Tether is similar, which leads to market volatility.

Figure 5. Impulse and response
3.3 GARCH model results

In the GARCH model of Bitcoin, all the variables have a remarkable influence on the return of the Bitcoin. The logarithmic number of new daily confirmed cases is negative and its lag one-order term is positive. In detail, when the percentage of the new daily confirmed cases or its lagging term increases one, the conditional variance of the Bitcoin model will decrease by 0.2603 or increase by 0.2354. And the impact on the return of the Ethereum is similar but the lag one order for the logarithmic number of new daily confirmed cases is larger. The conditional variance of the Ethereum model will reduce by 0.9023 or increase by 0.6993 if the new daily confirmed cases or its lag one-order term increase by 1%. As for the return of the Tether, the influence of the logarithmic number of new daily confirmed cases and its lag one phase are not significant. It is concluded that the variance equation also shows that the COVID-19 has led to the fluctuation of the yield of Bitcoin and Ethereum. But it does not affect the fluctuations of the Tether cryptocurrency.

| Table 4. GARCH model, variance equation |
|-----------------------------------------|
|                                          |
|                                         |
| (1) Bitcoin (2) Ethereum (3) Tether      |
| ARCH (-1) 0.2494*** (0.0458)            |
| GARCH (-1) 0.1327*** (0.0390)           |
| Ln newly confirmed cases T=0            |
| -0.1253*** (0.0120)                     |
| T=-1                                     |
| 0.2354*** (0.0280)                      |
| Constant                                 |
| -3.3668*** (0.1463)                     |

4. Discussion

This article finds that the COVID-19 pandemic promotes the increase in the price of electronic cryptocurrencies and leads to the volatility of their yields during this period. This is consistent with previous literature conclusions presented by Bo Lan and Lei Zhuang in 2021 which suggests that the COVID-19 pandemic fluctuates significantly, and the fluctuation in the digital currency market has an evident phase influence, resulting in various fluctuations in performance [7]. In addition, the article finds that the impact of the COVID-19 pandemic has different degrees of impact on the prices and yields of different electronic cryptocurrencies.

This article finds that COVID-19 raises the price of Bitcoin and the short-term impact of new global diagnoses on Bitcoin is positive, and it remains volatile after that and eventually disappears. It is consistent with previous literature conclusions presented by Ender Demir in 2020 and John W. Goodell in 2021[8, 11]. COVID-19 has a positive impact on electronic cryptocurrencies in the later stages and drives the price of bitcoin up. Also, in this study, the COVID-19 influences the price of Ethereum, but it is more manifested that the epidemic has caused fluctuations in the yield of Ethereum; The impact on the price of Tether has no economic significance. This reflects the fact as the theory presented by Muhammad Abubakr Naeem in 2020 that the impact of the COVID-19 on the electronic crypt market was mainly felt in Bitcoin and Ethereum while tether is subject to relatively little influence [9].

This paper also analyzed the impact of the three electronic cryptocurrencies according to the stage of development of the COVID-19, based on the time series and quantitative methods which are different from any previous study. This fills a gap in the research analysis and investment benefits of specific cryptocurrency developments in the context of humanity's long struggle with the COVID-19 and
provides some directional advice and reference for subsequent investment choices. This article analyses its phased impact on electronic cryptocurrencies in the context of humanity’s current common challenge, namely the quest for common development in coexistence with the new crown epidemic. It also illustrates the extent to which the prices and yields of three electronic cryptocurrencies (Bitcoin, Ethereum, and tether) have changed, providing information to support market investment in the current economic climate.

Future research can be carried out from three aspects. First, as mentioned earlier, since the outbreak of the COVID-19, it has been repeated worldwide. So, the impact of the COVID-19 pandemic is long-term and extensive. Further research could work on the long-term impact on the investment decision. Secondly, there are multiple channels for the indirect effects of the COVID-19 pandemic, but this is difficult to identify in empirical studies, and this also needs further research. In the end, in addition to the economic downturn caused by the COVID-19 pandemic, electronic cryptocurrencies have also been affected by the policy to varying degrees. There are many more aspects that deserve consideration and in-depth study.

5. Conclusion

Coronavirus disease 2019 (COVID-19) with a highly contagious and lethal nature, has become a global infectious disease since its outbreak. The worldwide economy has been impacted to diverse degrees because of periodic outbreaks and mutations of COVID-19 in various countries around the world, particularly in the real sector. However, under the influence of COVID-19, electronic cryptocurrencies are behaving extremely differently than traditional commodities. Therefore, this article looks at the global epidemic from the COVID-19 outbreak to the Russian-Ukrainian conflict, using financial models like ARMAX to examine the impact of the COVID-19 on three electronic cryptocurrencies: bitcoin, Ethereum, and tether.

As a result of the research, it is found that there is a clear phasing of the impact of the COVID-19 pandemic on electronic cryptocurrencies. There is a large impact on electronic cryptocurrencies in the early stages of the outbreak, driving up prices and increasing the level of yield volatility. Over time, the impact of the COVID-19 pandemic becomes less severe, and the volatility of electronic cryptocurrencies' yields becomes progressively more subdued. Of the three electronic cryptocurrencies, Bitcoin and Ether were more significantly affected by the impact of the COVID-19. The impact of the COVID-19 pandemic is not significant for Tether.

The empirical results clearly illustrate that the COVID-19 resulted in an increase in the price of electronic cryptocurrencies and increased volatility in their yields during this period. The study conducts a quantitative analysis of three cryptocurrencies using a time series of Bitcoin, Ether, and Tether's particular developments. This is extremely enlightening for investing behavior in the currency market under the influence of the COVID-19 epidemic. When investors have a better understanding of this, prudent investment choices will also benefit a thriving global economy, which is the paper's initial objective.

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