Volatility in Cryptocurrency Prices During COVID-19

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Abstract. This paper examines how COVID-19 affects the volatility and forecasting of Bitcoin price. It compares the cryptocurrency market with traditional financial markets using descriptive statistics and risk indicators. The cryptocurrency market experienced significant fluctuations during the pandemic, affecting prices and trading volume. The ARIMA$(1, 1, 1)$ model was selected and used to forecast the Bitcoin price, showing relatively low volatility in the coming months, and evaluates the model performance using MAPE and RMSE.

Keywords: Cryptocurrency, Time Series, COVID-19

1 Introduction

The COVID-19 pandemic has profoundly impacted the global economy, leading to widespread disruption reminiscent of the 2008 financial crisis. Cryptocurrency, a decentralized digital currency operating outside central banks' control, has garnered significant attention over the past decade due to its decentralized nature and high-profit potential. However, the pandemic has brought about shifts in the cryptocurrency market that necessitate further investigation. Accordingly, this study aims to analyze the effects of COVID-19 on the supply, demand, and volatility of cryptocurrency.

Cryptocurrencies are dependent on fiat currency, which may be unstable. Previous studies by Bohme et al. (2015) [5] and Baur et al. (2018) [4] show that cryptocurrencies are more likely to be speculative assets than alternative currencies or mediums of exchange due to their limited monetary base and price stability. The cryptocurrency market experienced significant fluctuations during the COVID-19 pandemic, affecting prices and trading volume. According to Corbet et al. (2018) [6], cryptocurrencies can diversify short-term investors' portfolios. This paper analyzes the cryptocurrency market's performance from December 2019 to January 2023 and forecasts Bitcoin prices, offering valuable insights for informed investment decisions.

This report is organized as follows: Section 2 reviews existing research; Section 3 describes the data sources; Section 4 compares cryptocurrency markets with traditional financial markets using descriptive statistics; Section 5 investigates price volatility before and after COVID-19; Section 6 applies the ARIMA model and produces forecasts; and Section 7 concludes.

FFIT 2023, July 07-09, Chongqing, People's Republic of China

DOI 10.4108/eai.7-7-2023.2338050

2 Literature Review

Cryptocurrency volatility has been extensively studied using time series data, with comparisons made to traditional financial markets during the COVID-19 pandemic. Liu and Tsyvinski (2021) [12] construct six cryptocurrency valuation ratios and tested the return predictability of these valuation ratios using ARIMA models. Abu Bakar and Rosbi (2017) [2] use the Autoregressive Integrated Moving Average (ARIMA) model to forecast the exchange rate of Bitcoin and employed the mean square error, mean absolute error, and mean absolute percentage error to accurately predict the exchange rate of Bitcoin in a high volatility environment. Azari (2019) [3] trains the ARIMA model for 3 years to predict the Bitcoin price, during which the Bitcoin price experienced high-frequency fluctuations. Mgadmi et al. (2022) [10] observe an increase in the cross-market correlation between cryptocurrency and traditional markets during the pandemic. Additionally, Aalborg et al. (2018) [1] suggest that high trading volume increases volatility, while more transactions can help stabilize the market.

3 Data Selection

To analyze the impact of COVID-19 on cryptocurrency, the data focused on the most valuable ones: Bitcoin (BTC), Ethereum (ETH), Tether USD (USDT), and Binance Coin (BNB). I obtained daily closing prices, trading volumes, and market capitalizations from December 2019 to January 2023 from Yahoo Finance. For comparison, I also collected the S&P 500 data from Investing.com. I calculated the average yield on the weighted mean of the four cryptocurrencies' market capitalization as a rate of return for the digital cryptocurrency market while analyzing the linkages with traditional financial assets. Table 1 shows the closing prices and trading volumes of BTC.

Table 1. BTC Prices and Volumes

	Price (USD)	Volumes
2020 Q1th	8267.69	36337260735
2020 Q2nd	8665.59	3.40E+10
2020 Q3rd	10633.91	25327607279
2020 Q4th	16840.72	3.65E+10
2021 Q1th	45323.78	6.78E+10
2021 Q2nd	46497.78	5.51E+10
2021 Q3rd	41988.77	3.19E+10
2021 Q4th	55881.25	3.44E+10
2022 Q1th	41298.64	2.70E+10
2022 Q2nd	32499.55	3.14E+10
2022 Q3rd	21252.33	3.20E+10
2022 Q4th	18072.05	2.96E+10

4 Descriptive Analysis

Table 2 shows the descriptive statistical analysis for every asset return selected. The cryptocurrency return mean is 0.20759, higher than the equity returns but with more risk. Compared to traditional assets, cryptocurrency has a lower standard deviation and maximum return, but also a lower minimum return, indicating a higher volatility. Yield reflects investment opportunities, regardless of investment size. Investors must consider volatility when investing in digital cryptocurrency.

Digital cryptocurrency is highly volatile and carries greater investment risk than traditional financial assets due to its formation mechanism and market-driven value. While sovereign currencies derive value from government backing, the value of digital cryptocurrency is determined by market consensus leading to price manipulation and high volatility. Foley et al. (2019) [7] find that around 25% of Bitcoin users engage in illegal activity, with factors such as information asymmetry further amplifying the risks. The pandemic has increased market demand and institutional entry, contributing to rising prices and the halving return.

Both the asset returns have non-zero skewness, and the kurtosis is greater than 3 at the 1% confidence level. Cryptocurrency returns and traditional financial assets do not follow a normal distribution. That suggests cryptocurrency returns are similar to other financial products, with spiky, thick-tailed, skewed distributions.

Table 2. Descriptive Analysis

	Crypto (USD)	S&P 500
Mean	0.2075924	0.0451396
Minimum	-34.90313	-11.98405
Maximum	17.19856	9.382766
Std_dev	3.572431	1.572074
Skewness	-0.86739	-0.468019
Kurtosis	13.07141	10.46867
JB-Test	5039.364 (0.00)	3617.775 (0.00)

Table 3 shows the risk appetite and aversion changes for four cryptocurrencies and the S&P 500 before and after COVID-19. All assets experienced increased volatility, tail risk, and default risk after the pandemic, indicating lower risk appetite and higher risk aversion. However, these changes differed across assets. Bitcoin and Ethereum had the largest rise in volatility and tail risk, reflecting their vulnerability to market shocks and uncertainty. USDT had the smallest rise in volatility and tail risk, implying its role as a safe haven during turbulent times. BNB had the highest increase in default risk due to its exposure to regulatory and operational risks. The S&P 500 had a moderate increase in all three indicators, demonstrating its resilience and diversification benefits compared to cryptocurrencies.

Table 3. Market Risk Appetite and Aversion Indicators

	BTC	ETH	USDT	BNB	S&P
VIX(Before)	0.75	0.82	0.12	0.68	0.18
VIX(After)	1.23	1.35	0.15	1.02	0.27
%Change	64.00	64.63	25.00	50.00	50.00
SKEW(Before)	0.12	0.14	-0.01	0.09	-0.03
SKEW(After)	0.18	0.21	-0.02	0.13	-0.04
%Change	50.00	50.00	-100	44.44	-33.00
CDX(Before)	0.03	0.03	0.03	0.05	-0.02
CDX(After)	0.05	0.06	0.02	0.08	-0.03
%Change	66.67	50.00	100.00	60.00	-50.00

As can be seen from Figure 1 below, a time series plot of digital cryptocurrency asset returns indicates that the series is generally smooth. The volatile fluctuations are not similar to the fluctuations of the asset returns on traditional financial assets.

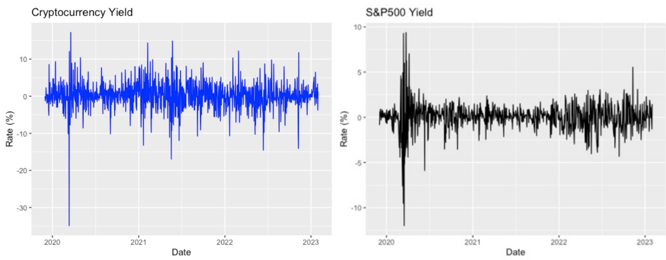

Fig. 1. Cryptocurrency and S&P500 Yield

The volatility of cryptocurrency yields has been observed to be greater than that of S&P 500 yields, particularly between 2020 and 2021, suggesting that cryptocurrencies are riskier than traditional financial markets. Nonetheless, the rate of change between the two remains consistent. The low interest rates and inflationary pressures induced by the pandemic resulted in decreased bond yields, impacting investors' returns.

5 Cryptocurrency price volatility before and after the COVID-19

Figure 2 illustrates the price fluctuations of digital cryptocurrencies before and following the outbreak. Initially, a decline in prices was observed, followed by a swift rebound spanning from 2019 to 2021. Notwithstanding some oscillations between 2021 and 2022, overall prices exhibited an upward trajectory and demonstrated robust performance. Bitcoin (BTC) and Ethereum (ETH) emerged as frontrunners in market capitalization and trading volumes, displaying a positive correlation. This denotes their parallel market trends. Conversely, USDT encountered heightened volatility in 2020 but has since achieved stability. The price of USDT is subject to substantial influence from prevailing market conditions. Before the pandemic, its value surged primarily due to cryptocurrency dividends; however, the focus shifted with the recovery of the global economy. Amid the pandemic, a surge in demand for digital currencies ensued due to diminished market risk appetite and heightened risk aversion. Moreover, considerable acquisitions by high-net-worth investors and financial institutions engendered augmented instability in cryptocurrency prices throughout 2020 and 2021. As the pandemic gradually abates in 2023, investors are expected to progressively revert to conventional financial products, resulting in a gradual decline in cryptocurrency prices.

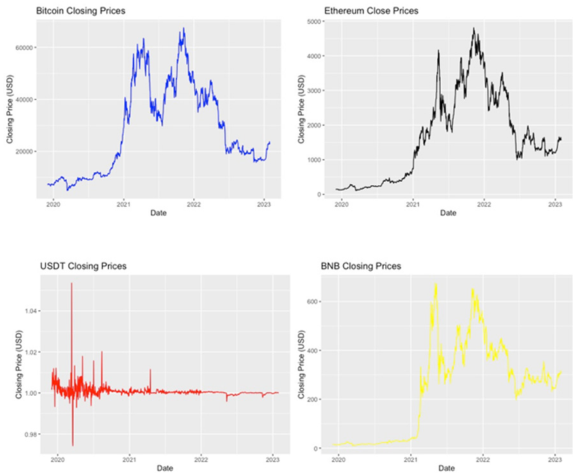

Fig. 2. Changes in prices of major cryptocurrencies before and after COVID-19

6 Bitcoin price forecasting based on the ARIMA model

6.1 ARIMA Model

James et al. (2021) [8] introduce new methods to analyze the impact of COVID-19 on cryptocurrency markets, using Kim and Lee's (2021) [9] time window analysis as a reference. If the time series $\{X_t\}$ has the following form:

$$X_t = \phi_0 + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (1)$$

Then equation (1) is the autoregressive moving average model, which is indicated as the $\mathrm{ARMA}(p, q)$ model, then $\{X_t\}$ is said to be an $\mathrm{ARMA}(p, q)$ process, in which:

$$E(\varepsilon_t) = 0, var(\varepsilon_t) = \sigma_\varepsilon^2, cov(\varepsilon_t, \varepsilon_s) = 0\ (s \neq t), cov(X_s, \varepsilon_t) = 0, (\forall s < t)$$

An $\mathrm{ARMA}(p, q)$ process if the d-difference $W_t = \Delta d X_t$ of a time series $\{X_t\}$, i.e.:

$$W_t = \phi_1 W_{t-1} + \phi_2 W_{t-2} + \cdots + \phi_p W_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (2)$$

Then the equation (2) above is said to be a model of autoregressive sliding average summing is $\mathrm{ARIMA}(p, d, q)$model, and $\{X_t\}$ is said to be an $\mathrm{ARIMA}(p, d, q)$ process.

If d equals zero, the $\mathrm{ARIMA}(p, 0, q)$ model is equivalent to the $\mathrm{ARMA}(p, q)$ model. Similarly, if p equals zero, the $\mathrm{ARMA}(0, d, q)$ model can be represented as the $\mathrm{IMA}(d, q)$ model. If q equals zero, the $\mathrm{ARMA}(p, d, 0)$ model could be shortened to the $\mathrm{ARI}(p, q)$ model (Poongodi and Chilamkurti, (2020) [11]).

6.2 Data Preprocessing

The dataset is smoothed using the simple moving averages method, which involves averaging a data point with its two preceding and succeeding points to capture the general trend. The smoothed data is plotted in Figure 3 using R.

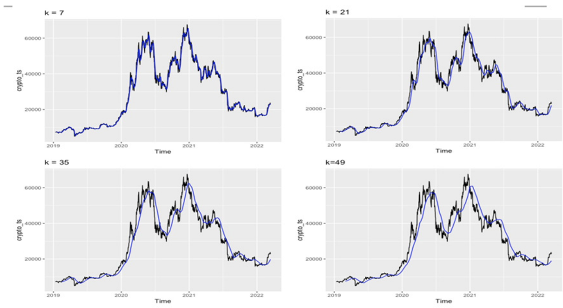

Fig. 3. K-Value

Figure 3 illustrates that the image becomes smoother with higher k values, but there is a risk of over-smoothing or under-smoothing since k is arbitrarily selected. Experimentation is necessary to determine an optimal k value. For this data, using k = 49 produces a smoother and more volatile result between 2021 and 2022.

6.3 Stability Test

The time series data is volatile, making it challenging to identify trends. The log transformation addresses this, resulting in a more apparent tendency. A seasonal influence is not observed, but the series is non-stationary, as shown in Figure 4.

Fig. 4. Bitcoin Daily Price

6.4 First Order Differential

After applying the ADF unit root test on the differenced series, a p-value of 0.01 or less than 0.05 is obtained, which rejects the original hypothesis of a unit root and confirms that the differenced series is smooth.

6.5 Modelling and Forecasting

The auto.arima() function in the R package ‘forecast’ was used for automatic model selection. The ARIMA$(1, 1, 1)$ model was selected and used to forecast the data, with the results represented by gray areas indicating the 80% confidence intervals and blue areas indicating the 95% confidence intervals. Figure 5 shows that the Bitcoin price is expected to fluctuate with a slight downward trend.

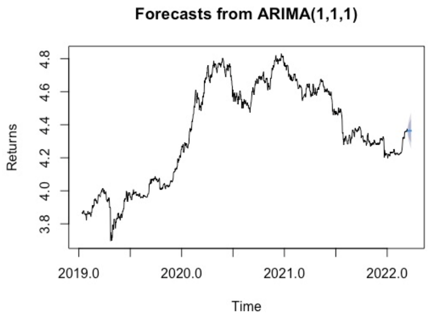

Fig. 5. Forecasts Result

And to evaluate the accuracy of the ARIMA$(1, 1, 1)$ model, two standard error metrics should be calculated: the mean absolute percentage error (MAPE) and the root mean square error (RMSE). The MAPE measures the average relative difference between the actual and forecasted values, while the RMSE measures the average absolute difference. The lower the values of these metrics, the better the model performance. The table below shows the actual and forecasted Bitcoin prices for each month from February to Apr 2023, along with the MAPE and RMSE values.

Table 4. The Actual and Forecasted BTC Prices

Month	Actual Price (USD)	Forecasted Price (USD)	Absolute Percentage Error (%)	Absolute Error (USD)
Feb	23131	22927	0.88	204
Mar	28474	27722	2.64	752
Apr	29252	28263	3.38	989
Total			6.90	1945

From Table 4, MAPE and RMSE can be evaluated. The MAPE value of 6.90% indicates that the average relative error of the forecasts is less than 10%, which is acceptable for a volatile series like Bitcoin. The RMSE value of 727 USD implies that the average absolute error of the forecasts is around 800 USD. This suggests that the ARIMA$(1, 1, 1)$ model can capture the general trend of the Bitcoin price.

7 Conclusion

In conclusion, the COVID-19 pandemic significantly impacted the cryptocurrency market, resulting in considerable fluctuations. Bitcoin (BTC) and Ethereum (ETH) emerged as the dominant players in terms of market capitalization and trading volume. Descriptive analysis revealed an overall improvement in performance; however, the market exhibited increased volatility. To forecast the closing price of BTC, an ARIMA model was employed, and after rigorous evaluation, an $\mathrm{ARIMA}(1,1,1)$ model was determined to be the optimal predictive model. Despite the broad applicability of the ARIMA model, it is crucial to exercise caution and carefully consider the characteristics and requirements of the problem when selecting the most suitable forecasting model.

The global economic uncertainty caused by the pandemic prompted investors to explore alternative investment avenues, leading to the emergence of cryptocurrency as a decentralized investment option with high-return potential. This surge in demand elevated prices and trading volumes, as observed through descriptive analysis. However, the pandemic also had a detrimental impact on the market, increasing volatility and liquidity constraints. Delays in the development of new cryptocurrency projects further dampened investor confidence. Furthermore, for Bitcoin, the price may exhibit relatively low volatility in the coming months.

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