Study of the Impact of Chinese Policies and Regulations on Bitcoin

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Abstract. Bitcoin is an emerging digital virtual currency with both decentralization, high degree of freedom and high bookkeeping efficiency, and the transaction scale of its market has developed rapidly in recent years. This paper selects the closing price of Bitcoin from May 2015 to August 2022, divides the data into two groups to establish a GARCH model based on the date of promulgation of the Bitcoin ban, and determines the impact of the regulation on the fluctuation of Bitcoin transactions by comparing the volatility characteristics of the two sets of models. This study is conducive to determining the direction and size of the impact of some policy changes on bitcoin fluctuations, and has a reference effect on the determination and adjustment of bitcoin-related policies and regulations.

Keywords: Bitcoin GARCH model yield fluctuations

1 Introduction

1.1 Research Background

In recent years, digital currency occupies a considerable position in Internet finance, and the Yingwei Finance website shows that as of 2022, there are more than 5,000 types of digital virtual currencies, more than 20,000 trading markets, and the total market value has reached 199.512 billion US dollars, and the bitcoin transaction volume has always accounted for more than 80% since 2018. As the most typical digital currency, Bitcoin has quickly become a hot investment in the context of Internet finance since its emergence. Bitcoin's transaction process is guaranteed by blockchain technology, each part of the block stores different information, and this information is strictly encrypted and cannot be changed, deleted, and there will be no hidden danger of information loss, so the transaction process of Bitcoin is often traceable. Bitcoin transactions can only be based on the consent of both parties, which provides a certain guarantee for the security of transactions. It can be used as a virtual currency to participate in transactions between Internet users, and its content can include various commodities, such as stock, debt futures, housing property rights, etc. The anonymity and convenience of Bitcoin's transaction operations have made it highly sought after by many Internet users who pursue

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privacy. After the covid-19 epidemic, the economic downturn has triggered the pessimism of capital holders about the future economy, investors in various countries are actively looking for safe-haven assets, bitcoin as a new type of digital virtual currency, since its emergence has risen considerably, although there have been many declines, but the overall situation continues to rise strongly.

Bitcoin has attracted a large number of safe-haven funds into the market, the transaction scale is expected to further expand during the epidemic. Bitcoin's price volatility is very intense, and the influencing factors and mechanisms of many abnormal fluctuations are difficult to define. At present, the policies promulgated by governments for Bitcoin are limited, the research on bitcoin yields at home and abroad is relatively scarce, and bitcoin investment still contains unknown risks. Clarifying the influencing mechanism and direction of Bitcoin fluctuations is not only conducive to investors avoiding the investment risks brought about by these influencing factors, but also provides certain theoretical support for policy makers and provides suggestions for the measures and directions of Bitcoin supervision.

1.2 Literature Review

At present, the academic community has put forward many views on the influencing factors of Bitcoin's yield volatility, the study tends to be comprehensive. Yilei Shi (2020) [1] has concluded that there is no obvious lag in good news by establishing a generalized autoregressive condition heteroscedasticity model (GARCH) simulation and event analysis method, the bearish news is more likely to be predicted by the public, and the Bitcoin market will fluctuate sharply due to various news released by the government. Zhou Wanling (2020) [2] used the GAUCHAR model and the ARJI family model to investigate the fluctuations of Bitcoin before and after the crash, and found that there was a jump fluctuation behavior in the bitcoin yield jumping fluctuation, and the jump intensity would increase with the price rise, with time variability and agglomeration, but the asymmetry was not obvious. Xie Wenhao (2022) [3]used the MF-ADCCA method to find that the stronger the liquidity of Bitcoin, the more violent the price fluctuations, and the stronger the degree of multiple fractals of the volume-price relationship; The lower the liquidity, the weaker the degree of multiple fractals. Some scholars believe that policy changes have a large impact on bitcoin yield volatility. The empirical study of the mixing model established by Bai Jiancheng (2022) [4] found that the EPU index has a significant impact on the volatility of the bitcoin market and Bitcoin will be affected by economic policy uncertainty from various countries; Zhao Tingting (2022) [5] constructed a time-varying parameter vector autoregressive (SV-TVP-SVAR) model of stochastic volatility, arguing that the direction of the impact of economic policy uncertainty on bitcoin prices varies with time, and the impact of economic policy uncertainty on bitcoin prices after 2018 has a long-term effect. Wang Hongtao (2022) [6] established the VEC model and used the unit root test, cointegration test, ANOVA to analyze the price fluctuations of Bitcoin, the results showed that there was a significant irrational price bubble in the Bitcoin price, the irrational bubble could be reduced but could not be eliminated.

In summary, the current stage of research has basically done relatively perfect research on the influencing factors of Bitcoin volatility, and laid a solid foundation for the price prediction and further research, but there has not been much argument for the mechanism and effect of the specific impact of influencing factors on Bitcoin. The purpose of this paper is to analyze the impact of the ban on the volatility of the Yield of the Chinese Bitcoin market.

2 Sources of Data

In order to clarify the impact of the ban on its fluctuation effect, this paper selects the closing price of Bitcoin on the New York Stock Exchange from 2015 to 2022, uses the date of the bitcoin ban (September 4, 2017) as the node to build a model to analyze the price fluctuations of bitcoin.

Before building the model, a descriptive statistical analysis of the daily closing price of Bitcoin is established, and the analysis results are shown in Table 1.

Table 1. Descriptive Statistical Analysis of Bitcoin (Self-drawn)

	Median	Minimum	Mean	Maximum	Standard Deviation
Before	598.5	216	996	4840	1045.02
After	9858	3251	19656	68412	17684.4

From the chart, it can be found that the descriptive values of the data have been significantly improved, indicating that the development trend of Bitcoin has been rapid since its emergence, the price transition of more than ten times has been achieved in a short period of time. The standard deviation of the two groups of samples reached 1045 and 17684 respectively, indicating that the price of Bitcoin fluctuated greatly, and the price volatility after the ban was far greater, and the price was significantly reduced. Bitcoin price fluctuations before and after the ban are generally similar, but the specific volatility still needs to be analyzed after modeling.

3 GARCH model

The GARCH model (Generalized autoregressive conditional heteroskedasticity model), also known as the generalized autoregressive condition heteroscedasticity model, is suitable for the prediction and analysis of fluctuations in financial time series data. GARCH(p,q) contains an autoregressive term and a moving average term, p is the lag order of the GARCH term, q is the lag order of the ARCH term. Since the price of Bitcoin is subject to its volatility, the GARCH-M model allows positive and negative asset yields to have an asymmetrical effect on volatility, which can explain the volatility aggregation characteristics of the trading series of financial assets, and can well describe the risk premium phenomenon. This paper selects the GARCH-M model to study the price volatility of Bitcoin, where M represents the conditional mean of the target financial asset. The mean equation and the variance equation of the GARCH model are set to:

$$Y_t = \alpha_1 + \beta_1 Y_{t-1} + \beta_2 \varepsilon_{t-1} + \beta_3 \varepsilon_{t-2} + \varepsilon_t \quad (1)$$

$$\sigma_t^2 = \alpha_2 + \beta_4 \varepsilon_{t-1}^2 + \beta_5 \sigma_{t-1}^2 \quad (2)$$

4 Empirical analysis

4.1 Stationarity test

Before the model was constructed, the ADF test and PP test were used to determine the stationarity of the data series, and after testing, the p-value of the data before the ban was 0.3433, and the p-value of the data after the ban was 0.4149, and the two sets of raw data were not stable. Using the R language ndiff() to determine the data difference order, the time series plots of the price data after the first order difference are as follows:

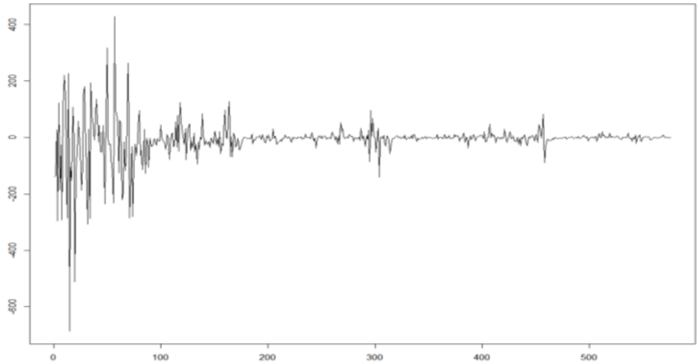

Fig. 1. Time series plot of first-order differential data before the ban was enacted (Self-drawn)

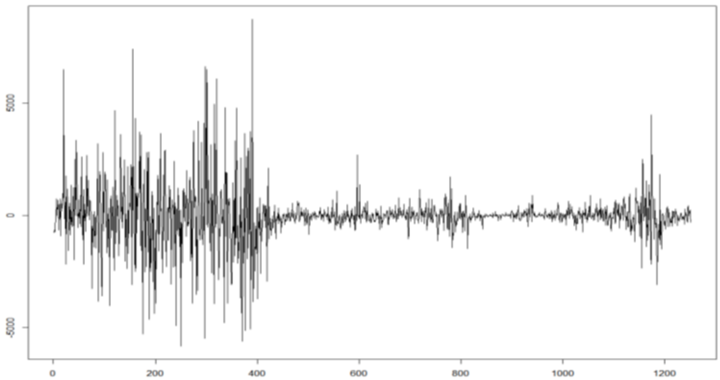

Fig. 2. Time series plot of first-order differential data after the ban was enacted (Self-drawn)

The stationarity of the data is retested after the first-order difference, and both pass the stationarity test, indicating that the two sets of first-order differential data are stable.

4.2 Build the model

Simulation using auto.arima() can determine the lag order of the data, the mean equation before the Bitcoin ban can be set to ARMA(0,1), the variance equation is set to GARCH(1,1), and the distribution model can be adapted to the generalized error distribution; The mean equation after the ban is set to ARMA(3,2), the variance equation is set to GARCH(1,1), and the distribution model is still a generalized error distribution. The white noise is tested by Ljung-Box test for the residual terms of the mean equation of the two sets of processed data in R language, and the test results are as follows:

Table 2. White Noise Test (Self-drawn)

	Lagging Order	p-value
Before the ban was enacted	5	0.2674
	9	0.9837
After the ban was enacted	5	0.9777
	9	0.9805

The test results show that the two sets of data cannot reject the null hypothesis under the 5th and 9th order tests, the residual is white noise, there is no autocorrelation, and the fit effect of the two sets of data is better.

To test the hysteresis order of the model, the AKaike information criterion (AIC) is an important tool for determining the hysteresis order in time series data analysis, in general, the smaller the value of the AIC, the more appropriate the hysteresis order. The fitted distributions of the standardized residual data of the two sets of data were replaced by the partial student distribution, the normal inverse Gaussian distribution, the Johnson reparametric SU distribution, and the good fit of these distributions was compared.

Table 3. Lagging Order Tests Before the Ban is Enacted (Self-drawn)

Distribution Name	Maximum likelihood value	AIC value
Generalized error distribution	-2478.079	8.629
Partial student distribution	-2500.250	8.706
The positron-inverse Gaussian distribution	-2484.690	8.652
Johnson reparametricsualized SU distribution	-2490.813	8.673

Table 4. Lagging Order Tests Before the Ban is Enacted (Self-drawn)

Distribution Name	Maximum likelihood value	AIC value
Generalized error distribution	-9707.149	15.537
Partial student distribution	-9721.383	15.559
The positron-inverse Gaussian distribution	-9711.162	15.543
Johnson reparametricsualized SU distribution	-9715.119	15.549

Table 5. Pearson Goodness of Fit Test Before the Ban Is Enacted (Self-drawn)

	P-value			
group	sged	sstd	nig	jsu
20	0.004	0.000	0.019	0.002
30	0.010	0.000	0.049	0.003
40	0.027	0.000	0.044	0.013
50	0.010	0.000	0.133	0.007

Table 6. Pearson's Goodness of Fit Test after the Ban was enacted (Self-drawn)

			P-value	
group	sged	sstd	nig	jsu
20	0.213	0.002	0.157	0.052
30	0.264	0.002	0.348	0.043
40	0.677	0.043	0.113	0.360
50	0.421	0.017	0.576	0.203

For the pre-ban data, by comparing the goodness of fit of four different distributions, it can be seen that the generalized error distribution and the positive and inverse Gaussian distribution have the best fit effect on the residuals of the data, the AIC values of the two distributions are compared. The generalized error distribution of 8.629 is less than the 8.652 of the positive and inverse Gaussian distribution, the great likelihood value of the generalized error distribution is the largest, so the fitting effect of the generalized error distribution is better than others; for the data after the ban, the generalized error distribution and the positive and inverse Gaussian distribution have a better fit effect on the residuals of the data, and the AIC values of the two distributions are also compared, the generalized error distribution of 15.537 is less than 15.543 of the positive and inverse Gaussian distribution, and the great likelihood of the generalized error distribution is the largest among the four distributions , so the fitting effect of the generalized error distribution is better than that of several other distributions.

If the conditional distribution model of both sets of data is set to a generalized error distribution, before the ban, the mean equation and the equation of variance estimated by the GARCH model are:

$$Y_t = -0.579 + 0.028Y_{t-1} + \varepsilon_t \tag{3}$$

$$\sigma_t^2 = 5.387 + 0.264\varepsilon_{t-1}^2 + 0.735\sigma_{t-1}^2 \tag{4}$$

Table 7. Pre-ban data parameter testing (Self-drawn)

	Estimate	Std.Error	t	Pr(>|t|)
mu	-0.57904	0.041605	-13.918	<0.01
ma1	0.02839	0.000777	36.532	<0.01

omega	5.3870	0.53106	10.144	<0.01
alpha1	0.26443	0.008002	33.043	<0.01
beta1	0.73457	0.018978	38.707	<0.01

After the ban, the mean equation and the variance equation are:

$$Y_t = 2.176 - 0.550Y_{t-1} - 0.743Y_{t-2} - 0.004Y_{t-3} + 0.587\varepsilon_{t-1} + 0.751\varepsilon_{t-2} + \varepsilon_t \quad (5)$$

$$\sigma_t^2 = 1535.200 + 0.131\varepsilon_{t-1}^2 + 0.868\sigma_{t-1}^2 \quad (6)$$

Table 8. Data parameter test after the promulgation of the ban (Self-drawn)

	Estimate	Std.Error	t	Pr(>|t|)
mu	2.17570	3.92170	0.55479	0.57904
ar1	-0.55025	0.00949	-57.961	<0.01
ar2	-0.74348	0.05108	-14.556	<0.01
ar3	-0.00446	0.00419	-1.0651	0.28684
ma1	0.58718	0.01123	52.282	<0.01
ma2	0.75075	0.04782	15.701	<0.01
omega	1535.2	778.12	1.9729	0.04850
alpha1	0.13090	0.01714	7.6359	<0.01
beta1	0.86810	0.01512	57.425	<0.01

5 Conclusion

In this paper, the R language is used to establish and analyze the model, and the GARCH model is established by establishing the closing price of bitcoin in the New York Stock Exchange market before and after the ban, the impact of this change on the volatility of bitcoin yield is compared and analyzed. Firstly, the ADF test and PP test stationarity test were carried out on the two sets of data, the two sets of data were found to be unstable, the first-order difference between the two sets of data was carried out again, and it was found that the two sets of data were stable at this time. Then determine the lag order， build models and equations, compare the models to determine the effect of the ban on the fluctuations of bitcoin.

Both sets of model equations above can better reflect the volatility effect of bitcoin returns, and the models have informative opinions in explaining and predicting the volatility condition of bitcoin. Comparing the two sets of mean and variance equations, we can find that the coefficient beta1 of the GARCH term is larger than the coefficient alpha1 of the ARCH term for both sets of data, indicating that the longer lagged influencing factors factors in bitcoin trading have a greater impact on volatility and the market is more effective in transmitting information. The coefficients of the GARCH terms of the models before and after the ban are close to 1, indicating that there is significant heteroskedasticity in the return volatility profile of the two data sets and that the impact of regulations on bitcoin is somewhat persistent. The GARCH coefficients of the data after the Bitcoin ban are larger, and the difference between the GARCH coefficients and the ARCH coefficients is larger than the difference before the Bitcoin ban, so the market transmission efficiency of the volatility impact term has improved after the Bitcoin ban, and the level of Bitcoin volatility has increased. As an internationalized virtual currency, the impact of a single country's policy on it is limited, and as the trading volume in China shrinks, the impact on Bitcoin becomes smaller.

This paper is informative in understanding the expected impact of Bitcoin volatility by policy versus the implementation of related regulations. China has long been adamant about banning bitcoin trading due to the difficulty of regulating bitcoin and the fact that issuance is not subject to government control. This paper finds that the implementation of regulations has had an impact on bitcoin return volatility, increasing the heteroskedasticity of bitcoin returns, and the impact on volatility is persistent. Bitcoin prices are simultaneously affected by economic policy uncertainty around the world, and China should attempt to regulate across regions and expand the scope of regulation to control the impact of Bitcoin on China.

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