The Impact of Macro Regulatory on Cryptocurrency Fluctuation: Evidence from China and the US

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Abstract. Bitcoin is the highest market capitalization product among virtual currencies today, attracting investors from all over the world. The attitudes and policies of governments towards bitcoin are a key concern for investors, and policy changes may have some impact on the bitcoin market. In this paper, the main topic is the changes in bitcoin market returns and volatility for different periods (one week, two weeks, and 1 month) after the U.S. and China proposed policies that have a negative impact on bitcoin by using an ARMA-GARCH model. The study shows that in the long-term perspective, the seemingly devastating policies did not generate much volatility in the overall market to shake investors' long-term investment enthusiasm. This study provides countervailing evidence to support investors who are overly concerned about Bitcoin's reduced investment value due to tough government regulation, boosting investor confidence.

Keywords: Macro regulatory; Cryptocurrency; Fluctuation.

1. Introduction

Bitcoin, a cryptocurrency, was first proposed by Satoshi Nakamoto in 2008 in the wake of the global financial crisis and out of frustration with centralized banking and disbelief in fiat currencies that were vulnerable to macroeconomic fluctuations. He introduced the concept of Bitcoin in his white paper "Bitcoin: A Peer-to-Peer Electronic Cash System", which solved the centralization problem that previous electronic currencies could not escape. After a series of developments, Bitcoin gradually became the largest part of the cryptocurrency market share, breaking the $10,000 mark for the first time in August 2020 and soaring to an all-time high of nearly $70,000 in November 2021, with a total market capitalization of over $2 trillion, making it one of the most sought-after investment products. Because of its potential excess returns, investors and experts are always looking for factors that influence bitcoin price fluctuations, and in the past, Andrew Urquhart has judged the price and returns of bitcoin by studying market efficiency [1]. Bouri et al. studied relations between Bitcoin and conventional investments by studying return and volatility spillovers between equities, stocks, commodities, currencies, and bonds in bear and bull market conditions. The relationship between Bitcoin prices and conventional assets was derived [2]. Samuel Kwaku Agyei and Anokye Mohammed Adam et al. concluded that VCRIX can have a significant impact on cryptocurrencies by studying the cryptocurrency-implied volatility index (VCRIX) between Bitcoin and five other different virtual currencies, guiding investors to hedge effectively [3]. Mehmet Balcilar and Elie Bouri et al. study the causal relationship between trading volume and Bitcoin returns and volatility [4].

In addition to this, many believe that even though Bitcoin is a distributed, decentralized virtual currency, government controls or policies will still have an impact on its price. Julei Ba Lin Chen et al. study the price volatility of bitcoin after the Chinese government issued a bearish bitcoin policy in 2017 [5]. Gang Liu, Juan Liu, and Wanrong Tang have studied the changing patterns of bitcoin prices in the presence of changing national policies within different countries [6]. As mentioned in their study, it is necessary to focus on the attitudes of the two countries with the largest bitcoin holdings and transactions toward bitcoin, and therefore, in this study, the same focus is placed on the impact of U.S. and Chinese policies on the volatility of bitcoin prices. Bitcoin was in a completely unregulated and "wild" environment in its early days, and in 2014 the IRS officially launched a tax on Bitcoin. However, due to the anonymous nature of Bitcoin, the government has no way of knowing the true amount of Bitcoin held by the taxpayers and cannot know the transaction records and specific information of the taxpayers. Specific information, there are still a large proportion of people according to not report or there is underreporting concealment phenomenon, so in the subsequent 2016, the IRS asked the large U.S. exchange Coinbase to provide personal information, and in July-August 2018, the U.S. Internal Revenue Service (IRS) to more than 10,000 U.S. cryptocurrency holders were sent 6173, 6174 or 6174-A three kinds of letters The recipients were asked to sign to certify their compliance with U.S. tax laws and advised to pay their taxes, and under relevant U.S. laws, citizens who refuse to assume their tax obligations face tax fraud, for which the IRS can impose a variety of penalties, including criminal prosecution, imprisonment for five years, and fines of up to $250,000 [7]. And the policy on virtual currency tax returns, which was revised again in 2019, simultaneously alerts cryptocurrency investors who fail to properly declare their income and pay taxes, urging them to assume their tax obligations related to cryptocurrencies. The 2019 amendments and additions are the clearest definition of cryptocurrency and the most detailed and stringent tax reporting requirements ever imposed by the U.S. government, not only on investors but also on miners, wallets, exchanges, and DeFi companies. The new regulations have drawn widespread attention from cryptocurrency practitioners and investors in the United States.

In mainland China, as the importance of the financial system grows, so does the need for the Chinese government to control it. Cryptocurrencies, especially Bitcoin, are a challenge to China's systemic financial risk because the Chinese central bank cannot track the flow of funds through these assets, which greatly enhances the risk of Chinese assets flowing overseas while providing a good way for money laundering. To avoid such risks, Chinese officials have banned initial token offerings (ICOs) since the release of the 2017 Announcement on Preventing the Risks of Token Issuance and Financing, and the exchange of domestic digital currencies for legal tender has been completely halted, and their circulation and sale within China is prohibited. However, the state supports the blockchain technology used for digital currencies. However, at this time, many people can still trade cryptocurrencies such as Bitcoin through overseas exchanges, and the cryptocurrency industry in China is still a "gray area" and mining activities in China are still not restricted. In May 2021, the Bank of China announced by the Internet Finance Association of China, the China Banking Association, and the China Payment and Settlement Association on Preventing the Risk of Speculation in Virtual Currency Trading, which prohibits financial and payment institutions from accepting cryptocurrencies as payment and settlement instruments or providing services and products related to cryptocurrencies. If consumers suffer any losses in cryptocurrency investment transactions, they are required to bear the losses themselves. In September of the same year, the Bank of China issued another Notice on Further Preventing and Disposing of the Risk of Speculation in Virtual Currency Trading, which declared that virtual currencies do not have the same legal status as legal tender and that any virtual currency-related business activities are illegal. The notice also considers foreign virtual currency exchanges providing services to Chinese residents via the Internet as illegal financial activities. Since nearly 80% of bitcoin transactions are managed through data centers set up in China, and China was the second-largest country in terms of bitcoin trading volume before this, the Chinese government's policy will have an impact on bitcoin and in the international market, bitcoin prices took a big dive on the day the policy was released, with the market blowing up to nearly $6 billion.

In summary, the policies of the U.S. and Chinese governments may have some impact on the price of Bitcoin. Taxes imposed by the government and government crackdowns and bans may have a negative investment orientation for Bitcoin investors in the short term, but this study is more concerned with its far-reaching impact and hopes to derive its long-term impact on the market by looking at price data before and after the policy release nodes.

For guidance on the research methodology, the main choice was to use a GARCH model, which has been extensively worked on before, such as Bohte and Rossini et al. in their study of Forecasting of Cryptocurrencies by Bayesian Time-Varying Volatility model [8], and Ghani and Rahim's ARMA-GARCH model [9]. Meanwhile, Yilei Shi conducts a study on bitcoin volatility characteristics and value investment by using GARCH model [10]. All of the above work provides ideas for the methodology of this study.

The following parts of the paper are organized as follows: The second part is the research design, including data sources, calculation of returns, ADF test, and model specification, and the third part is the empirical results and analysis, including the results of the ADF test, the way to fix the order in constructing the model and the results of the final ARMA-GARCH model estimation.

2. Research design

2.1 Data sources

The data used in this paper are downloaded from investing.com, which is an authoritative and widely accessed financial data website to ensure that our research data are authentic and valid. Because this paper studies the impact on bitcoin prices when policies are released in two different countries, the United States and China, this step needs to find two sets of data, the first set is the virtual currency reporting guidelines issued by the IRS and the time point of the warning and in July 2019. The second set of data is the time point and May 2021 when the Chinese government completely bans the legal existence of virtual currencies within mainland China. This research selects the data for the six months before and after the policy enactment date as our research sample.

2.2 ADF test

Before building the model, the first step is to test the stationary of the data. Since this research mainly studies the orientation of investors, the price of bitcoin should be converted into a yield before processing.

$$x_t = \frac{y_t - y_{t-1}}{y_t} \tag{1}$$

In (1) $\boldsymbol{x_t}$ represents the return in period t and y_t represents the bitcoin price in period t.

The stationarity of the series is determined by testing whether it has a unit root by the following equation.

$$x_t = c_t + \mu x_{t-1} + \sum_{i=1}^{p-1} \rho_i \Delta x_{t-i} + e_t \tag{2}$$

In (2) c_t is a constant, e_t is the residual, μ is a coefficient representing the effect of the previous period's return on this period, and $\sum_{i=1}^{p-1} \rho_i \Delta x_{t-i}$represents the past trend. In this test, the original hypothesis is H_0: $\mu = 1$ = 1 and the alternative hypothesis is H_1: μ < 1.

2.3 ARMA-GARCH specification

An ARMA-GARCH model is developed for simultaneously predicting Bitcoin's return and volatility. The ARMA model takes both the AR model and the MA model to predict future returns through autocorrelation and past perturbations and then derives the following ARMA (p, q) model.

$$x_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i x_{t-1} + a_t - \sum_{i=1}^{q} \theta_i a_{t-i} \tag{3}$$

In (3), φ_0 is a constant, p and q are non-negative integers, φ_i represents the degree of influence of the return at period i in the past on the return in the current period, and a_t is the disturbance term $\sum_{i=1}^{q} \theta_i a_{t-i}$ represents the sum of the disturbance terms in the past q periods.

For the GARCH model, three exogenous variables are designed, which are the returns one week after the policy is introduced, two weeks after the policy is introduced and six months after the policy is introduced, and they are used as dummy variables, and the specific GARCH (1,1) model is designed as follows.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \sigma_{t-1}^2 + D_1\beta_1 + D_2\beta_2 + D_3\beta_3 \tag{4}$$

In (4) $\alpha_1 \varepsilon_{t-1}^2$ is part of GARCH, $\gamma_1 \sigma_{t-1}^2$ is a simple autoregression of the GARCH term being σ_t^2, D_1, D_2, D_3 represents the three dummy variables mentioned above, and the coefficient β_1, β_2, β_3 represent the significance of the effect of the dummy variables on the model.

3. Empirical Results and Analysis

3.1 The results of the smoothness test

As shown in table1, the ADF test indicates that the price of bitcoin is unstable with a p-value greater than 0.05 for the data before and after the issuance of different policies in the US and China, while the yield data is significantly smooth for both periods again with a p-value much less than 0.05.

Table 1. ADF test

Variables	t-statistic	p-value
Price		
Bitcoin, 2019	-0.452	0.9852
Bitcoin, 2021	-2.056	0.5707
Yield		
Bitcoin, 2019	-19.127	0.0000***
Bitcoin, 2021	-13.614	0.0000***

Therefore, both data sets of returns are eligible introduced variables in the ARMA-GARCH model, as both are smooth.

3.2 ARMA identification

For the two data sets, this part first applies PACF and Varsoc tests to them respectively to determine the order of the AR model.

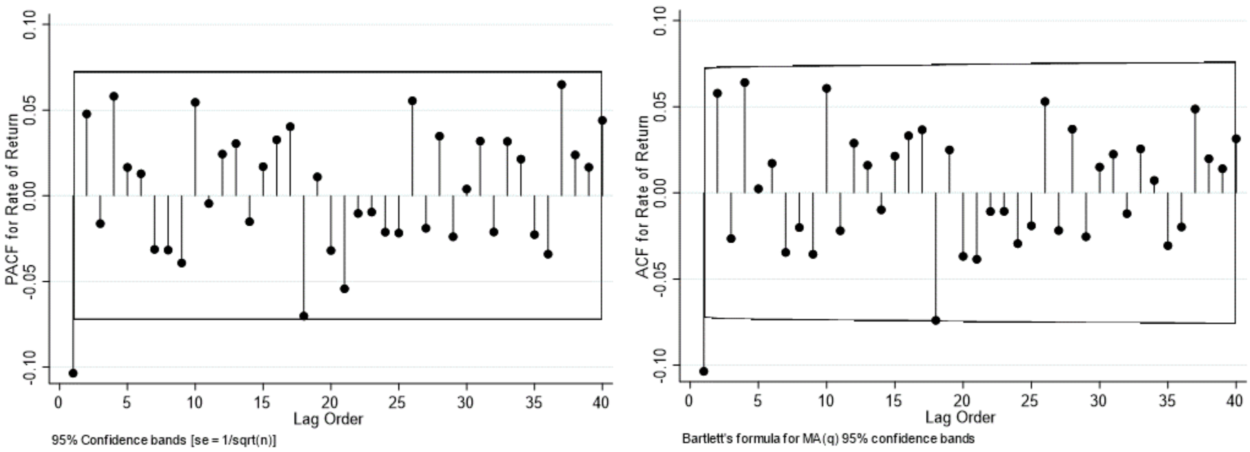

Figure 1. ARMA identification, 2019

Note: In the left panel of Figure1 the y-axis is the dependent variable, which is the PACF of the logarithm of bitcoin returns, and the x-axis is the number of lags. The y-axis in the right panel is the dependent variable, which is the ACF of the logarithm of bitcoin returns, and the x-axis is the number of lags.

In the left panel of Figure 1, it can be seen that PACF starts to decline after lag=1 while the Varsoc test of Table 2 shows that the minimum number of periods from HQIC and SBIC is lag=1.

Table 2. AR identification ,2019

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	1265.7				.0017	-3.5179	-3.5154	-3.5115
1	1269.45	7.4962*	1	0.006	.0017*	-3.5255*	-3.5206*	-3.5128*
2	1270.26	1.6171	1	0.203	0.0017	-3.5250	-3.5176	-3.5059
3	1270.34	0.1699	1	0.68	0.0017	-3.5225	-3.5126	-3.4970
4	1271.5	2.3196	1	0.128	0.0017	-3.5229	-3.5106	-3.4911
5	1271.62	0.2404	1	0.624	0.0017	-3.5205	-3.5057	-3.4823
6	1271.68	0.1132	1	0.737	0.0017	-3.5178	-3.5006	-3.4733
7	1272.03	0.6958	1	0.404	0.0017	-3.5160	-3.4964	-3.4651
8	1272.4	0.7408	1	0.389	0.0017	-3.5143	-3.4921	-3.4570
9	1272.94	1.0934	1	0.296	0.0017	-3.5130	-3.4884	-3.4493
10	1274	2.1041	1	0.147	0.0017	-3.5132	-3.4861	-3.4431
11	1274	0.0139	1	0.906	0.0017	-3.5104	-3.4809	-3.4340
12	1274.22	0.4259	1	0.514	0.0017	-3.5082	-3.4762	-3.4254

Note: Standard errors are reported in parentheses, and the estimated results are rounded-up to 4 digits after the decimal point. ***, **, and * indicate the level of significance of 1%, 5%, and 10%, respectively.

At this point, it can conclude that for the 2019 data, the AR model is ordered to the first period.

Now, this part starts to determine the order of the MA model for 2019 by the ACF test. The right panel of Figure 1 shows that the ACF starts to decline in the 95% confidence interval after lag=1 period. Therefore, the same lag order is taken for the MA model.

For the 2021 data, we take the same identification approach.

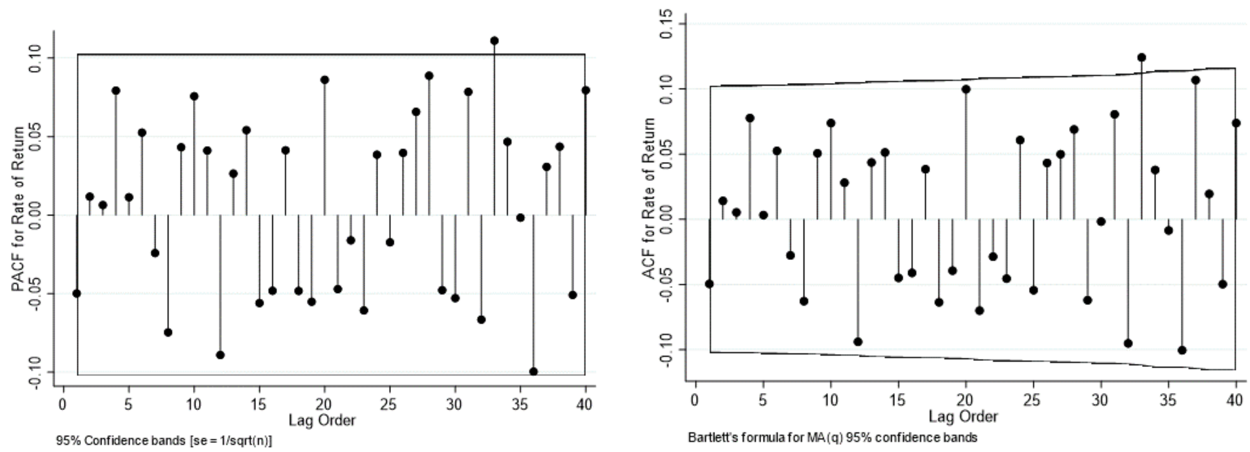

Figure 2. ARMA identification, 2021

Note: In the left panel of Figure2 the y-axis is the dependent variable, which is the PACF of the logarithm of bitcoin returns, and the x-axis is the number of lags. The y-axis in the right panel is the dependent variable, which is the ACF of the logarithm of bitcoin returns, and the x-axis is the number of lags.

First of all, in the order of the AR model, the minimum value of HQIC and SBIC from Table 3 is 0 order lag, which is unrealistic, but from the left panel of Figure 2, we get the maximum value of PACF at lag=33, so we use the 33rd period as the order of AR for 2021 data.

Table 3. AR identification, 2021

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	613.483				.0018*	-3.4701*	-3.4658*	-3.4592*
1	614.057	1.1474	1	0.284	0.0018	-3.4677	-3.4590	-3.4458
2	614.125	0.1362	1	0.712	0.0018	-3.4624	-3.4493	-3.4296
3	614.151	0.0520	1	0.82	0.0018	-3.4569	-3.4395	-3.4131
4	615.453	2.6035	1	0.107	0.0018	-3.4586	-3.4368	-3.4038
5	615.495	0.0851	1	0.77	0.0018	-3.4532	-3.4270	-3.3875
6	616.033	1.0755	1	0.3	0.0018	-3.4506	-3.4201	-3.3739
7	616.121	0.1763	1	0.675	0.0018	-3.4454	-3.4105	-3.3578
8	617.147	2.0512	1	0.152	0.0018	-3.4455	-3.4063	-3.3470
9	617.45	0.6072	1	0.436	0.0018	-3.4416	-3.3980	-3.3321
10	618.33	1.7596	1	0.185	0.0018	-3.4409	-3.3930	-3.3204
11	618.64	0.62055	1	0.431	0.0018	-3.4370	-3.3847	-3.3056
12	620.058	2.8356	1	0.092	0.0018	-3.4394	-3.3827	-3.2970

MA model also uses the ACF test, and the right panel of Figure 2 shows that also the maximum value of ACF is obtained at lag=33

The maximum value of ACF is obtained at lag=33. Therefore, lag=33 is applied in model 2021.

3.3 ARMA-GARCH estimation results

From Figure 3 and Figure 4, there is a relatively significant aggregation of bitcoin returns in the two time periods 2019 and 2021, but whether the aggregation is statistically significant requires further testing.

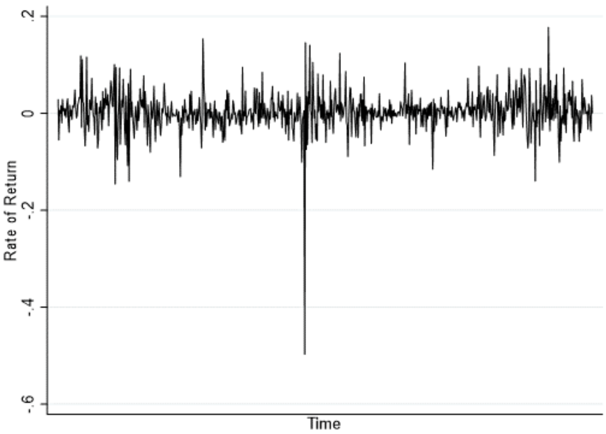

Figure 3. Yield trend, 2019

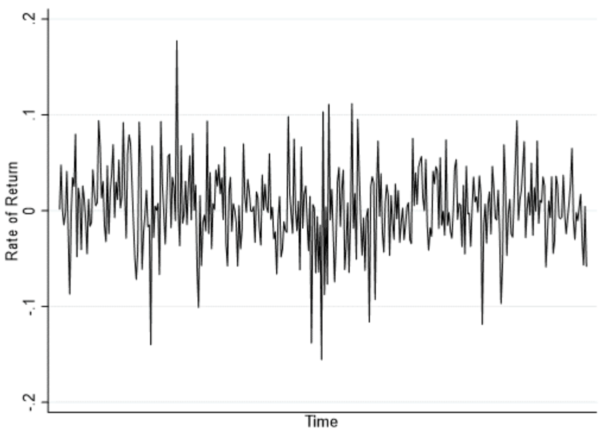

Figure 4. Yield trend, 2021

The ARCH and GARCH terms indicate the ARCH and GARCH effects of the return series, respectively. From the estimation results of the variance equation, the ARCH term of bitcoin return is significant in both periods and GARCH is also significant in 2019. Accordingly, the GARCH cluster model can be established.

From the estimated coefficients of the dummy variables, bitcoin returns do not produce greater daily volatility within one week, two weeks, or after the tax on bitcoin transactions in the U.S. in 2019. Similarly, China's policy of restricting bitcoin transactions in 2021 does not produce greater volatility in bitcoin returns. The immediate column (4) estimate is significantly positive at the 10% level, but it also lacks statistical significance.

Table 4. ARMA-GARCH estimation results, variance equation

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	2019			2021		
Dummy						
D1	-187.755***	-1849.073***	-121.7912***	1.7262*	1.6989	1.6770
	(.9199)	(.7597)	(.6103)	(.9145)	(1.1903)	(1.1994)
D2		1.7579*	2.4438***		.0297	.2173
		(.9918)	(.8751)		(.7914)	(.8106)
D3			-.4246			-.3297***
			(.4673)			(.1233)
GARCH						
ARCH (-1)	.1894***	.1011**	.1021***	-.0379**	-.0374**	-.0378***
	(.0311)	(.0409)	(.0393)	(.0190)	(.0193)	(.0190)
GARCH (-1)	.7899***	.9002***	.8963***	-.1515	-.1632	-.1590
	(.0280)	(.0279)	(.0275)	(.6928)	(.6938)	(.6966)
Constant	-9.0530***	-9.8539***	-9.5694***	-6.2388***	-6.2332***	-6.0861***
	(.1853)	(.5328)	(.6077)	(.5887)	(.5878)	(.5708)

Note: D1 in the dummy variables represents the base future week on the date of policy issuance, D2 represents the data for the next two weeks after the base date, and D3 represents the data for the next six months after the base date. Discussion

Compared with the previous study by Julei Ba et al [5], this paper compares the volatility of bitcoin returns after the release of a single policy in both the US and China. And compared with the study of Liu Gang, Liu Juan, Tang Wanrong, et al [6], the events selected in this paper have a higher degree of impact on the development of bitcoin and theoretically have a greater impact on the bitcoin market and investor confidence. Also, the models used in the above studies are single AR models, while this paper uses ARMA-GARCH models and makes improvements in the research methodology. Compared with Leiyi Shi's study [10], this research only focuses on the time frame after the event and does not focus on the "prediction period" in Shi's study, i.e., the market movement before the policy release.

The above estimation results show that there is no significant impact on long-term market volatility from the restrictive policies on bitcoin trading in the US or China. This is contrary to the big jump in cryptocurrency prices and people's reaction to negative news when the policy was first enacted. There are three possible reasons for this phenomenon.

(1) The first is the decentralized nature of Bitcoin. In Zheyu Li's study, it is mentioned that this "free" nature can greatly reduce government or state intervention [11]. Before the Chinese government's total ban on virtual currency, mainland China was the largest bitcoin mining country in the world and 80% of transaction data was stored by Chinese servers. After the total ban in May 2021, bitcoin mining activity shrank by 1/3 in a very short period, but then rebounded by 20% in the following July. August, and by October the impact of the emergence has largely offset, while mining activity in the US has almost doubled in that time. The decentralized nature of bitcoin ensures that it is not limited to a region, as long as there is a computer or computing power, it can be mined anywhere and circulated into the market promptly.

(2) Investor behavior in the US or Chinese markets alone is not enough to influence the entire market, and we may be overestimating the influence of a single regional market on the global market. It used to be thought that China accounted for 80% of the world's bitcoin trading volume and was an integral part of the virtual currency world, but it turns out that bitcoin trading can still be conducted in an orderly manner in other regions outside of mainland China.

(3) The impact of the policy is not strong enough for the U.S. tax supplementation policy. Compared to the high returns of bitcoin, the taxation is insignificant in terms of investor motivation, and most investors will still choose to accept the taxation and accept the rules to ensure they can continue to profit from bitcoin.

For investors, the empirical results of this paper conclude that the impact of policy on bitcoin return volatility is minimal in the long-term perspective, and legitimate investors need not worry about losing the value of their investment due to the sequestration of bitcoin in China and tax regulation in the U.S. As a global decentralized virtual currency, bitcoin is still widely accepted worldwide. (*It is also important to note that bitcoin investing is an extremely high-risk investment practice and investors can suffer significant losses)

4. Conclusion

The negative policies of the US and China on bitcoin do cause investors to panic in the short term and reduce investment transactions in the short term. This paper focuses on bitcoin returns and volatility one week, two weeks, and six months after the release of the policies in the US and China. The empirical results show that the impact of the policies mentioned in the introduction section on the returns and long-term volatility of the bitcoin market is not significant, bitcoin is still favored by most investors, and the bitcoin market is stable in the long term.

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