

A Study on the Relationship Between Bitcoin and Stock Market Volatility under Different Policy Environments — Comparison Between Chinese and US Markets

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ABSTRACT

The increasing integration of Bitcoin with traditional stock markets makes understanding its impact on stock market volatility crucial. This paper constructs a GARCH-MIDAS model using data from the Shanghai Composite Index, the S&P 500 Index, and Bitcoin to investigate Bitcoin's influence under different regulatory environments. The results show that Bitcoin has a significant negative relationship with the volatility of both Chinese and US stock markets, indicating that the relationship between Bitcoin and stock market volatility does not vary significantly across different regulatory environments.

KEYWORDS

Bitcoin; Stock Market; GARCH-MIDAS model

1. INTRODUCTION

Bitcoin, as a novel investment tool, has garnered extensive attention from both academia and market participants. The correlation between Bitcoin and traditional financial markets remains a controversial topic. Unlike traditional financial markets, such as stocks, bonds, and commodities, which are primarily influenced by macroeconomic factors like interest rates, inflation, and government policies, Bitcoin, being a decentralized cryptocurrency, experiences price fluctuations driven mainly by investor sentiment and market demand. Despite these differing influences, a correlation between Bitcoin and traditional financial markets can be observed under certain circumstances.

Notably, Roome [1] found that the correlation between Bitcoin and stock markets varies across different time scales and market environments. However, most current studies focus only on the relationship between Bitcoin and the stock market of a single country. There is a noticeable lack of literature comparing the correlation between Bitcoin and stock markets under different national regulatory environments. Consequently, this study seeks to address the following research question: What are the differences in the relationship between Bitcoin and stock market volatility across various regulatory environments?

To explore this, we employ the GARCH-MIDAS model to analyze Bitcoin's relationship with the overall stock markets of China and the United States since Bitcoin began stable trading. Furthermore, we segment the Chinese market into two sub-periods based on policy changes: 2013-2017 (a period characterized by individual Bitcoin trading only) and 2017-2023 (a period marked by the complete shutdown of Bitcoin platforms). This approach allows us to clearly compare the differences in Bitcoin's relationship with stock market volatility across different regulatory periods.

The findings indicate that Bitcoin's relationship with stock market volatility does not significantly differ between the two regulatory environments. For the overall sample, whether in China or the United States, stock market volatility does not increase significantly due to the popularity of blockchain technology underlying digital currencies like Bitcoin. Instead, stock market return volatility tends to stabilize. Specifically, during the 2013-2017 period in China, Bitcoin and stock market volatility had a positive but not significant relationship. In contrast, during the 2017-2023 period, the relationship between the two turned significantly negative.

In summary, this study offers several key contributions. Firstly, it provides policy insights by revealing the relationship between Bitcoin and stock markets under different regulatory environments, offering valuable references for policymakers. Secondly, it enriches financial market theory by elucidating the interaction between cryptocurrencies and traditional financial markets, particularly how Bitcoin, as an emerging asset, affects stock market volatility. Lastly, understanding the relationship between Bitcoin and stock market volatility is crucial for investors and asset managers to optimize portfolio allocation and risk management strategies. Investors can adjust their asset allocations under different regulatory environments to mitigate market volatility risks.

2. LITERATURE REVIEW

2.1. Bitcoin Characteristics

In recent years, Bitcoin has garnered increasing attention from investors, practitioners, and researchers. Many scholars have delved into the intricacies of this digital currency, exploring its impact across various domains. Through a review of literature on the nature of Bitcoin, we have identified three primary aspects that characterize its properties:

Firstly, with respect to Bitcoin's volatility, Köchling [2] demonstrates that utilizing high-frequency data improves the accuracy of Bitcoin volatility forecasts, with GARCH-type models showing good performance within this framework. Zhao Lei et al. [3] examined and predicted Bitcoin price fluctuations based on the log-periodic power law model. Secondly, concerning Bitcoin's profitability, Baur et al. [4] 's research demonstrates that Bitcoin returns are largely uncorrelated with traditional assets such as stocks and bonds, suggesting that Bitcoin can serve as an effective diversification. Duc et al. [5] found through variance decomposition that an increase in the price of gold relative to platinum leads to higher returns for Bitcoin, and the volatility in the gold and platinum markets affects Bitcoin's own volatility, with this relationship exhibiting time-varying dependence. Lastly, regarding Bitcoin's value at risk, Gkillas et al. [6] studied the tail behavior of the returns of five major cryptocurrencies and concluded that among them, Bitcoin and Litecoin pose the least risk.

2.2. Relationship Between Bitcoin and Stock Market

The interplay between Bitcoin and traditional stock markets has become a focal point of investigation. Scholars and market analysts alike are increasingly exploring how Bitcoin interacts with established stock markets. This inquiry stems from Bitcoin's emergence as a distinctive asset class with potentially unique correlations to conventional stocks. By delving into these dynamics, researchers seek to uncover insights into the diversification benefits, risk management implications, and broader economic ramifications of Bitcoin's relationship with stocks. Bouri, Molnár, and Azzi [7] utilized wavelet analysis to identify a negative correlation between Bitcoin volatility and global stock markets; however, this correlation may exhibit substantial variation across different time scales. Roome [1] suggested that under certain market conditions, Bitcoin may display co-movement characteristics with stock markets while exhibiting distinct patterns under other conditions. This underscores the potential for differing risk-return profiles for Bitcoin as an investment asset in varying market environments.

Meanwhile, Liu et al. [8] conducted a study using time-frequency analysis to investigate the association between Bitcoin price fluctuations and stock market volatility. The research revealed that Bitcoin price movements exhibit delayed effects on stock market volatility, with the correlation varying across different time frequencies. Luo Mei et al. [9] examined the relationship between Bitcoin returns and lagged Dow Jones Index returns, identifying a substantial connection between the Bitcoin market and traditional stock markets. Nadarajah et al. [10] performed a non-parametric analysis to explore the interdependent relationship between Bitcoin and major stock indices. Additionally, Holmes et al. [11] discovered complex dynamic linkages between the Bitcoin market and stockmarkets, suggesting that Bitcoin price movements can serve as leading indicators of anomalies within stockmarkets.

López-Cabarcos et al. [12] analyzed Bitcoin's behavior using GARCH and EGARCH models while studying how investor sentiment, S&P 500 returns, and VIX returns influence Bitcoin volatility. Their results demonstrated that during speculative periods, Bitcoin volatility becomes more unstable. Additionally, Garcia et al. [13] further explored the impact of Bitcoin market volatility on the S&P 500 index. Their investigation revealed that Bitcoin market volatility significantly affects the S&P 500 index, particularly during periods characterized by market turmoil or uncertainty. Moreover, Elie Bouri et al. [14] conducted a study focusing on examining the relationship between Bitcoin prices and the total index of the US stock market. They employed a vector autoregressive (VAR) model to assess the volatility of the S&P 500 composite index and its 11 sector indices. The findings from their research indicate an inverse relationship between Bitcoin prices and the actual volatility of the US stock market.

The existing research by various scholars on the relationship between Bitcoin and the stock market primarily focuses on three aspects: Firstly, as a novel digital asset emerging in the internet age, Bitcoin exhibits volatility and profitability characteristics. Its price is influenced by both internal and external market factors, leading to significant fluctuations that may result in systemic risk transmission to the stock market. Secondly, with the expansion of market trading volume and activity, coupled with accelerated economic and financial globalization, Bitcoin's impact on the stock market has increased. Thirdly, the correlation between Bitcoin and the stock market varies significantly across different time scales and market environments. Most current studies only examine the relationship between Bitcoin and a single country's stock market; there are few studies comparing correlations between Bitcoin and stock markets of different countries.

In contrast to the existing literature, this thesis will explore the nuanced relationship between Bitcoin and stock market volatility within the distinct regulatory environments of China and the United States. While previous studies have primarily focused on the correlations and co-movement between Bitcoin and traditional stock markets, this research aims to delve deeper into how these relationships are influenced by differing policy regimes. This analysis can aid investors and policymakers in more effectively evaluating risks, refining asset allocation strategies, and comprehending the repercussions of global economic policy changes on the market. The United States and China, as the two largest economies globally, possess extensive stock markets. Investigating Bitcoin volatility's impact on these two markets can offer a more comprehensive understanding of the relationship between the Bitcoin market and the global financial market. Additionally, both countries boast highly developed financial markets with well-established trading and regulatory systems, substantial investor bases, and significant international influence. Exploring these markets' responses to Bitcoin volatility can provide insights for other countries' financial markets [15].

Furthermore, the regulatory landscape in China and the United States diverges significantly. In 2013, the People's Bank of China and other financial entities prohibited financial institutions from engaging in Bitcoin transactions, marking the initial step in regulating cryptocurrency activities. Subsequently, in 2017, China implemented a ban on initial coin offerings and shuttered domestic cryptocurrency exchanges. Over the period from 2017 to 2023, China introduced several noteworthy bans and regulations pertaining to Bitcoin and other cryptocurrencies. These regulatory interventions are

designed to mitigate the transmission of risks from the Bitcoin market to other sectors of the financial markets in China.

In the US market, the regulatory framework is relatively flexible, albeit characterized by the implementation of several effective regulatory measures. In contrast to China's approach of imposing bans, the US government's regulatory measures aim to strike a balance, fostering innovation in the cryptocurrency sector while mitigating risks related to financial stability, consumer protection, and illicit activities.

Therefore, based on the analysis of Bitcoin's characteristics and the review of the aforementioned literature, this study will focus on the following aspects: Firstly, it will conduct a comparative study focusing on China and the United States to examine the relationship between Bitcoin and stock market volatility under different policy environments. Secondly, to further explore these effects, the study will segment the Chinese sample into two sub-sample periods based on distinct policy eras for comparative analysis.

3. EMPIRICAL RESEARCH

3.1. Model Construction

Traditionally, literature models and empirical studies on volatility have primarily relied on the GARCH model. However, the limitation of GARCH-type models lies in their inability to capture long-term volatility in financial markets due to their requirement of data at the same frequency. In response to this, Engle et al. [16] proposed the GARCH-MIDAS model to explore the relationship between stock markets and macroeconomic activities. Zheng et al. [17] applied the GARCH-MIDAS model to estimate and forecast volatility in the Chinese stock market based on macroeconomic fundamentals, finding a significant positive impact of macroeconomic fluctuations on stock market volatility. Wei et al. [18], using the GARCH-MIDAS model, separately investigated the impact of hot money on the overall Chinese stock market and on different industry sectors, revealing a significant positive effect of hot money on long-term volatility in the Chinese stock market. All the studies on the Chinese stock market utilizing the GARCH-MIDAS model mentioned above are based on macroeconomic variables. However, in recent years, Bitcoin has garnered widespread attention due to its decentralized nature, independent of sovereign governments, central authorities, and banking systems. Investigating the relationship between Bitcoin and the stock market by treating Bitcoin as a low-frequency variable (weekly) and stock indices as high-frequency variables (daily), and establishing a GARCH-MIDAS model, would present a novel and worthy topic for further exploration.

Firstly, Bouri [19] found that the frequency of matters for Bitcoin properties. According to Roome [1], the volatility characteristics of Bitcoin and stock indices may vary across different time scales. As an emerging digital asset, Bitcoin's price fluctuations are likely influenced by macroeconomic factors, market sentiment, and policy changes, which typically take longer to manifest. In contrast, stock indices, representing mature financial markets, are more immediately and visibly affected by daily news, economic data releases, and market sentiment. The GARCH-MIDAS model can simultaneously consider these long-term and short-term volatility characteristics within the same framework.

Secondly, according to Holmes et al. [11], the relationship between Bitcoin and the stock market may not be static but may change over time. The GARCH-MIDAS model can capture these dynamic relationship changes, helping investors and researchers better understand the contagion effects and linkage mechanisms between different markets.

In conclusion, using Bitcoin as a low-frequency variable and stock indices as high-frequency variables to establish a GARCH-MIDAS model can provide a more detailed and comprehensive

perspective on analyzing long-term impacts and volatility forecasting. This approach effectively captures the complex relationships between the data, enhances the accuracy of market volatility predictions, and deepens the understanding of dynamic relationships between markets.

Therefore, based on the research by Engle et al. [16], we introduced the Generalized Autoregressive Conditional Heteroskedasticity-Mixed Data Sampling (GARCH-MIDAS) model.

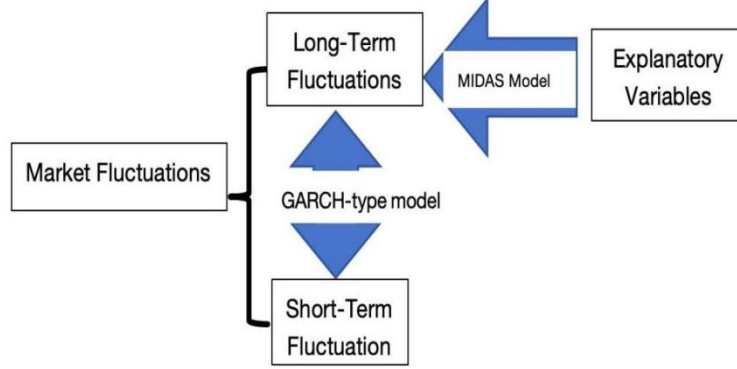


Figure 1. Model Overview

3.1.1. GARCH Model

The Generalized Autoregressive Conditional Heteroskedasticity model, proposed by Bollerslev (1986), is a method used for modeling volatility in financial time series. It captures the common phenomenon of "volatility clustering" in financial markets, where periods of high volatility tend to cluster together, as do periods of low volatility.

Let represent the return at time t , and represent a white noise series with zero mean and unit variance. The GARCH (1, 1) model can be expressed as:

$$r_t = \mu + \epsilon_t \quad (1)$$

$$\epsilon_t = \sigma_t z_t \quad (2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (3)$$

Here, μ is the constant term, σ_t^2 is the conditional variance, α_0 , α_1 and β_1 are non-negative parameters that satisfy $\alpha_1 + \beta_1 < 1$ to ensure the stability of the conditional variance. z_t is an independent and identically distributed standard normal random variable.

The model parameters can be estimated using the maximum likelihood estimation method. Given the return series $(\{r_t\}_{t=1}^T)$, the likelihood function is:

$$L(\mu, \alpha_0, \alpha_1, \beta_1) = \prod_{t=1}^T \frac{1}{\sigma_t} \phi\left(\frac{r_t - \mu}{\sigma_t}\right) \quad (4)$$

Where $\phi(\cdot)$ is the probability density function of the standard normal distribution. The log-likelihood function is:

$$\log L(\mu, \alpha_0, \alpha_1, \beta_1) = -\frac{1}{2} \sum_{t=1}^T \left(\log(2\pi) + \log(\sigma_t^2) + \frac{(r_t - \mu)^2}{\sigma_t^2} \right) \quad (5)$$

By maximizing the log-likelihood function, the parameter values can be obtained.

3.1.2. MIDAS Model

The Mixed Data Sampling (MIDAS) model, introduced by Ghysels, Santa-Clara, and Valkanov (2004), is used to model relationships between time series at different frequencies, such as high-frequency and low-frequency data.

Suppose we have low-frequency variable Y_t and high-frequency variable $X_{t,j}$, where Y_t denotes monthly data and $X_{t,j}$ denotes daily data. The MIDAS model can be represented as:

$$Y_t = \beta_0 + \beta_1 \sum_{j=0}^{m-1} \phi_j X_{t-j/k} + \epsilon_t \quad (6)$$

Where ϕ_j is the weight function used to capture the influence of the high-frequency variable, typically employing exponential decay weight functions such as Almon Lag or Beta Lag.

$$\phi_j = \frac{\exp(\theta_1 j + \theta_2 j^2)}{\sum_{i=0}^{m-1} \exp(\theta_1 i + \theta_2 i^2)} \quad (7)$$

$$\phi_j = \frac{j^{\theta_1 - 1} (m-j)^{\theta_2 - 1}}{\sum_{i=0}^{m-1} i^{\theta_1 - 1} (m-i)^{\theta_2 - 1}} \quad (8)$$

The estimation of MIDAS model parameters is typically achieved through nonlinear least squares or maximum likelihood estimation. The objective is to minimize the following objective function:

$$Q(\beta_0, \beta_1, \theta_1, \theta_2) = \sum_{t=1}^T (Y_t - \beta_0 - \beta_1 \sum_{j=0}^{m-1} \phi_j X_{t-j/k})^2 \quad (9)$$

The estimation of parameters can be obtained through optimization techniques such as gradient descent or quasi-Newton methods.

3.1.3. GARCH-MIDAS Model

The GARCH-MIDAS model, proposed by Engle, Ghysels, and Sohn (2013), is an integrated model that combines the GARCH model for modeling volatility in high-frequency data and the MIDAS model for modeling long-term trends in low-frequency data. This model is able to capture both short-term and long-term volatility characteristics, providing more accurate and flexible volatility forecasts. The model settings are as follows:

$$r_{i,t} - \mu = \sqrt{\tau_t g_{i,t}} \epsilon_{i,t}, \forall i=1, \dots, N_t \quad (10)$$

Among them, $r_{i,t}$ is the stock return rate on the i -th day of the t -th month, μ is the conditional mean, N_t is the total number of trading days per month, and $\epsilon_{i,t}$ is a random variable subjecting the conditional standard normal distribution. $\epsilon_{i,t} | \varphi_{i-1,t} \sim N(0,1)$, $\varphi_{i-1,t}$ is a collection of historical information on day $i-1$ of month t . $g_{i,t}$ is the short-term fluctuation component of the conditional variance on day i of month t , and subjects the GARCH(1,1) process, that is:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \quad (11)$$

Where $\alpha > 0$, $\alpha + \beta \leq 1$. τ_t represents the long-term component of volatility. In addition, only realized volatility is used to illustrate the GARCH-MIDAS model. The expression is as follows:

$$\ln(\tau_t) = m + \theta \sum_{k=1}^K \varphi_k(\omega) R_{t-k} \quad (12)$$

R is the rate of return of Bitcoin, and K is the lag order, $\varphi_k(\omega)$ is a weight equation constructed based on the Beta function. The expression is as follows:

$$\varphi_k(\omega) = \frac{(k/K)^{\omega-1}}{\sum_{j=1}^K (j/K)^{\omega-1}} \quad (13)$$

Equations (10) to (13) constitute the basic model of GARCH-MIDAS.

3.2. Empirical Analysis

3.2.1. Data Sources

We choose the daily closing price of Bitcoin as its price, and use the Shanghai Composite Index and the S&P 500 Index to represent the stock prices in China and the United States, respectively. The data for this study is obtained from CoinMarket Cap.com and Yahoo Finance.

Starting from the first launch of regulatory policies by the central bank, data from 2013 to 2023 are selected. Among them, the data sample from China consists of 2,435 entries, while the data sample from the United States consists of 2,517 entries. And for the Chinese data sample, due to the significant impact of the two major Bitcoin bans by the Chinese central bank in 2013 and 2017 on the Bitcoin market, we divided the data into two periods to examine how Bitcoin market volatility under different policy bans affects the Chinese stock market. The four samples are named CN-ALL, CN-1, CN-2, and US-ALL.

Table 1. Sample Division

Policy measures	Time period	Number of samples
Individual Bitcoin Trading Only	2013.12.31-2017.09.05	900
Complete Shutdown of Bitcoin Platforms	2017.09.06-2023.12.29	1535

Note: Considering that the Bitcoin market trades 7*24, we excluded all weekend and holiday data when referring to stock market data in this study.

3.2.2. Descriptive statistical analysis

Table 2. Statistical Description of Data after Preprocessing

	mean	Min	Max	Std	Var	skew	kurtosis
SSEC	0.0001	-0.0887	0.0560	0.013	0.0002	-1.06	7.61
BTC	0.0030	-0.8488	1.4742	0.063	0.0040	3.69	129.84
SP500	0.0004	-0.1277	0.0897	0.011	0.0001	-0.82	16.58

Note: SSEC, BTC, and SP500 represent the log-returns of the Shanghai Stock Exchange Composite Index, Bitcoin, and the S&P 500 Index, respectively. The data covers the period from December 31, 2013, to December 29, 2023, with daily frequency for the stock indices, while weekly frequency is used for Bitcoin.

Based on Table 2, the average returns of SSEC, BTC, and SP500 are all close to zero, but their volatility differs. The standard deviation and variance of BTC are 0.063 and 0.004 respectively, which are the highest among the three, indicating that its volatility is much greater than that of the stock market, and the investment risk is extremely high. In contrast, the volatility of SP500 returns is the lowest.

The return distribution of Bitcoin shows a significant right skewness, meaning that the distribution of returns extends longer to the right side. This implies that the positive returns (upswings) have been larger and more frequent than the negative returns (downturns). In other words, Bitcoin has experienced more significant upward price movements compared to its downward movements, indicating potential for high gains despite the inherent volatility. As observed in the data, the maximum return of Bitcoin (1.4742) is much higher than the minimum return (-0.8488). This suggests that high returns occur more frequently in Bitcoin. The kurtosis of Bitcoin returns (129.84) is much higher than that of the SSEC (7.61) and SP500 (16.58), indicating that the distribution of Bitcoin returns is much sharper, with more extreme values appearing in the tails. This implies that in the Bitcoin market, extreme return fluctuations occur more frequently, leading to higher market volatility.

3.2.3. Unit root test and Autocorrelation test

Table 3. Results of Data Testing

	Jarque-Bera	ADF	ARCH
SSEC	6920.614972*** (0.0000)	-9.4812329*** (3.87E-16)	301.589*** (0.0000)
BTC	1878805.326*** (0.0000)	-24.108892*** (0.0000)	39.2953*** (0.0000)
SP500	31881.61791*** (0.0000)	-16.538814*** (1.99E-29)	143.614*** (0.0000)

Note: (), denotes the test statistic p value; *, **, and *** represent significant rejection of the null hypothesis within the significance levels of 10%, 5%, and 1%, respectively.

According to the Jarque-Bera test, the returns of the Shanghai Composite Index, Bitcoin and the S&P 500 Index do not follow a normal distribution. The ADF test (stationarity test) shows that both the returns of the Shanghai Composite Index, Bitcoin and the S&P 500 index are within the level of 1%, which significantly rejects the null hypothesis that these three time series are stable and can be processed in the next step. The ARCH test (autocorrelation) results show that the return rate of both time series is within 1%, which can significantly reject the null hypothesis of unconditional heteroscedasticity, that is, both time series have autocorrelation, which is suitable for the modeling of GARCH class models.

3.2.4. Bitcoin's Relationship with Stock Market Volatility

Table 4 presents the fitted results of the GARCH-MIDAS model for four samples. μ represents the long-term estimate of stock return averages. α and β measure the contributions of short-term volatility changes to overall volatility, where α denotes the direct impact of recent short-term volatility on current volatility, and β reflects the influence of past volatility squared on current volatility. θ represents the parameter in the MIDAS model that measures the nonlinear effect of long-term components on volatility. m denotes the constant term for long-term volatility components, representing the baseline effect on long-term volatility in the absence of other variables. Lastly, w_2 is the weight parameter used for weighted calculation of long-term component variance. Our analysis primarily focuses on α , β , and θ .

Table 4. GARCH-MIDAS Fitting Result

	CN-ALL	CN-1	CN-1	US-ALL
μ	0.013	0.041	0.012	0.078***
	(0.020)	(0.038)	(0.026)	(0.015)
α	0.079***	0.054***	0.112**	0.190***
	(0.021)	(0.016)	(0.049)	(0.033)
β	0.915***	0.945***	0.845***	0.771***
	(0.022)	(0.017)	(0.063)	(0.035)
m	0.909	0.885	0.259	0.357
	(0.644)	(0.651)	(0.292)	(0.286)
θ	-1.009**	0.155	-0.647**	-1.296***
	(0.440)	(0.859)	(0.361)	(0.380)
w2	1.000**	2.329***	1.226	1.608***
	(0.394)	(0.417)	(1.077)	(0.256)
LLH	-3280.029	-1092.234	-1860.058	-2938.571
BIC	6606.222	2223.421	3763.113	5923.525
VAR_RATIO	14.446	0.093	14.982	

Note: LLH represents the maximum likelihood value (likelihood) in logarithmic form of the estimated parameter vector, BIC is the Bayesian information quasi-value, VAR_RATIO represents the ratio of variances, $VAR_RATIO = \text{var}(\log(\tau))/\text{var}(\log(\tau_{gt}))$, a measure usually used to quantify the relative importance of long-term components; *, **, and *** indicate significant rejection of the null hypothesis at the 10%, 5%, and 1% levels, respectively.

From the table, it can be observed that for the Chinese stock market, whether it is the full sample (CN-ALL), CN-1, or CN-2 sub-samples, the parameters α and β of the GARCH equation are significant at the 1% level, indicating a strong volatility clustering effect in the short term for the Shanghai Composite Index, and the sum of α and β is close to 1, consistent with the requirements of the model parameters.

For the full sample (CN-ALL), the value of the long-term component θ is -1.009 and significant at the 5% level, indicating Bitcoin volatility has a negative relationship with long-term Chinese stock market volatility, i.e., the Chinese stock market is affected by the Bitcoin market in the long term. Holding other conditions constant, the greater the volatility of the Bitcoin market, the relatively smaller the volatility of the Chinese stock market.

From 2013 to 2017 (CN-1), it is noteworthy that the parameter θ is not significant and is positive at 0.155. This indicates that while Bitcoin volatility increased during this period, the volatility of stock market also increased relatively. However, the impact on the volatility of the Chinese stock market in the long term decreased compared to the total sample period and was not significant. Therefore, the long-term impact on the volatility of the Chinese stock market during this period is relatively small.

From 2017 to 2023 (CN-2), the value of θ is -0.647 and significant at the 5% level. During this period, both the actual trading volume and trading prices of Bitcoin increased. Hence, this suggests a negative impact of the increase in Bitcoin trading volume and trading prices on the Chinese stock market. That is, the volatility of Chinese stock market does not increase significantly due to the heated trading of Bitcoin based on blockchain technology; instead, it tends to remain relatively stable. And according to table1, the sample size from 2017 to 2023 is almost twice that of 2013 to 2017, explaining why Bitcoin and the Chinese stock market are overall negatively correlated.

For the US market (US-ALL), the parameters (α , β) of the GARCH part are significant at the 1% level, with a θ value of -1.296. This indicates a negative impact of Bitcoin on the volatility of the US

stock market, implying an inverse relationship between Bitcoin and the actual volatility of the US stock market. This inverse relationship suggests that in the US context, Bitcoin may serve as a diversification asset or a hedge against stock market volatility. The statistical significance at the 1% level further emphasizes the robustness of this finding. Additionally, compared to the Chinese market, the impact of Bitcoin on the volatility of the US stock market is more pronounced.

4. CONCLUSION

This study uses the GARCH-MIDAS model to examine the relationship between Bitcoin and both the overall stock market of China and the overall stock market of the United States since its stable trading. Additionally, to delve deeper into the variations in Bitcoin's relationship with stock market volatility under different policy environments, the Chinese stock market is segmented into two sub-sample periods based on distinct policy phases: 2013-2017 (period characterized by individual Bitcoin trading only) and 2017-2023 (period marked by the complete shutdown of Bitcoin platforms).

The findings reveal that across the entire sample, Bitcoin exhibits a significant negative relationship with both the Chinese and American stock markets. This suggests that the stock market volatility tends to stabilize despite the heightened trading activity in Bitcoin and other digital currencies supported by blockchain technology. The results align with previous studies by Bouri, Molnár, and Azzi (2019), highlighting a negative correlation between Bitcoin volatility and global stock markets. Consistently, the findings are in line with Elie Bouri, Afees A. Salisu, and Rangan Gupta's (2023) conclusion that Bitcoin prices exhibit an inverse relationship with actual volatility in the US stock market.

In the Chinese context, from 2013 to 2017, Bitcoin's relationship with the Chinese stock market shows a positive but not statistically significant association. However, from 2017 to 2023, Bitcoin's impact on Chinese stock market volatility transitions to a notably significant negative relationship. These findings are consistent with Liu, Chen, and Wu's (2020) research, indicating that the correlation between Bitcoin price volatility and stock market volatility varies across different time periods and frequencies.

In summary, we observe that Bitcoin exhibits a noticeable relationship with the volatility of China's stock market, transitioning from a previously insignificant positive correlation to a significant negative correlation. This shift can be attributed to a series of stringent regulatory measures enacted by China concerning Bitcoin and cryptocurrencies post-2017, including the prohibition of ICOs, the closure of domestic cryptocurrency exchanges, and the crackdown on cryptocurrency mining and trading. These regulatory actions serve to mitigate financial risks and uphold market stability.

In the case of the US market, Bitcoin's relationship with stock volatility is negative, and this relationship appears to be more pronounced compared to the Chinese stock market. As outlined in the literature review section, the United States maintains a relatively lenient regulatory environment, aiming for a balanced approach that fosters innovation while mitigating risks. In conjunction with our findings, this suggests that within this permissive regulatory framework, the US stock market remains resilient to the tumultuous fluctuations of the Bitcoin market. Therefore, we conclude that the relationship between Bitcoin and stock market volatility remains consistent across different regulatory environments.

The similar positive effects brought about by the differing regulatory policies of the two countries may be attributed to variances in the maturity of their respective stock markets and investor behaviors. The US stock market is relatively more open compared to China's, and the regulatory environment surrounding cryptocurrencies in the US has changed, making Bitcoin more readily accepted and integrated into financial markets. As cryptocurrencies become increasingly mainstream and less susceptible to extreme speculative behavior, this integration may contribute to stabilizing stock market volatility.

In conclusion, governments and regulatory bodies worldwide should continuously monitor developments in the cryptocurrency market and flexibly adjust policies to adapt to evolving market conditions. Furthermore, different countries should formulate corresponding regulatory strategies based on their own national conditions and characteristics of their stock markets.

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