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Do Bubbles in the Bitcoin Market Impact Stock Markets? Evidence From 10 Major Stock Markets

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Abstract

In this paper, we examine the effect of explosive behaviors in the Bitcoin market on the top 10 largest stock markets of developed and emerging countries. The daily dataset, including the Dow Jones Industrial Index (DJIA), Nasdaq (NSQ), Shanghai Composite Index (SSE), Nikkei 225 (N225), Hang Seng Index (HSI), Shenzhen Composite Index (SZSE), Euronext Amsterdam Index (AEX), London Stock Exchange (LSE), Toronto Stock Exchange (TSX), and Bombay Stock Exchange (BSE), spans July 21, 2010, to December 9, 2022. We first investigate the existence of explosive price behaviors using the bubble detection test of Phillips and Shi and the results provide evidence of multiple bubble episodes, coinciding with the monetary policy actions of the FED and ECB. Then, we address the question of whether the explosive behaviors detected affect the variance of equity returns by employing a GARCH model. The impact is negative, albeit its magnitude and significance vary among stock indices.

Keywords

Bitcoin, cryptocurrencies, bubbles, stock markets, GSADF

Introduction

Asset bubbles are a critical issue for investors and other relevant authorities because they have unpredictable effects on the financial stability of an economy (Xiong et al., 2020). In financial markets, a bubble is defined as a continuous and systematic deviation of the market value of an asset from its fundamental value. These price fluctuations cannot be explained by fundamental factors (Diba & Grossman, 1988). Such deviations are primarily due to optimistic investor sentiment, which increases the aggregate demand for assets (Kyriazis et al., 2020). Studies that identify asset price bubbles generally have two steps. The first assesses the empirical characteristics of the asset price series. For this purpose, the bubble detection test by Phillips et al. (2015) is widely used. Secondly, since a bubble is defined as a deviation of prices from their fundamental value, any statement about asset price bubbles requires an understanding of the fundamental value of the underlying asset (Gronwald, 2021). Speculative bubbles occur primarily when investors consider selling digital currencies with limited supply, such as Bitcoin, above the price at which they were purchased (Geuder et al., 2019). Speculative bubbles can thus be described as a prolonged rise in asset prices followed by a fall in prices (Chan et al., 1998). Speculative bubbles have been the focus of attention of researchers, investors, and market regulators for many years. For this reason, numerous studies investigate the existence of bubbles in various markets. For example, bubbles have been identified in stock markets (see, e.g., Chan et al., 1998; Diba & Grossman, 1988; Homm & Breitung, 2012; Kılıç, 2020; G. Wu & Xiao, 2008), housing markets (see, e.g., Abraham & Hendershott, 1996; Mikhed & Zemčík, 2009;

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Shi, 2017), foreign exchange markets (see, e.g., Bettendorf & Chen, 2013; Meese, 1986; Woo, 1987; Y. Wu, 1995), crude oil prices (see e.g., Miller & Ratti, 2009; Su et al., 2017; Zhang & Yao, 2016), real estate markets (see, e.g., Herring & Wachter, 2003; Kim & Suh, 1993), and agricultural commodity prices (see, e.g., Adämmer & Bohl, 2015; Baldi et al., 2016; Gutierrez, 2013).

In recent years, the growing interest in cryptocurrency markets has led researchers (see, e.g., Cagli, 2019; Cheah & Fry, 2015; Corbet et al., 2018; Fry & Cheah, 2016; Gronwald, 2021; Kyriazis et al., 2020) to investigate the presence of speculative bubbles in cryptocurrency prices. Cryptocurrencies are among the most remarkable financial innovations of the last decade (Enoksen et al., 2020). Given their exceptional return potential and unpredictable sharp price drops (Shu & Zhu, 2020) during periods of extreme price increases (Cagli, 2019; Hakim das Neves, 2020; Makarov & Schoar, 2020), they have attracted considerable interest in financial circles as an alternative to traditional investment instruments. Schinckus et al. (2021) suggest that anonymous cryptocurrencies are very good assets in terms of diversification, while Ali et al. (2023) state that Bitcoin emerged as an alternative safe asset in 2008. Bitcoin, Ethereum, Tether, Ripple, and Litecoin are among the cryptocurrencies with the highest market values. However, with the rise of cryptocurrency investors, this list is continuously changing. Bitcoin was the first known cryptocurrency to be based on mathematical cryptology. It is an alternative to government-backed currencies (Cheah & Fry, 2015) and a decentralized digital currency (Corbet et al., 2019; Holub & Johnson, 2019) which originated in an article published by Nakamoto (2008). It ranks first among cryptocurrencies in terms of both market value and price. The main feature that differentiates Bitcoin from other payment methods and makes it popular is its remittance and transaction system which does not require third parties (Corbet et al., 2019; Dwyer, 2015; Faghih Mohammadi Jalali & Heidari, 2020). Bitcoin's background is blockchain technology, which offers key advantages, such as transparency of information, the ability to make international payments, the anonymity of users, no need for third parties, irreversible payments, no or low transaction costs, no transaction tax, and low risk of theft (Faghih Mohammadi Jalali & Heidari, 2020). Blockchain technology can be considered a combination of a network and a new way of managing databases (Schinckus, 2021). The increasing adoption of blockchain technology and its use in cryptocurrencies enables international investors to exchange cryptocurrencies 24/7 (Begušić et al., 2018). Baek and Elbeck (2015) state that Bitcoin is a flow that can replace financial institutions, an alternative to money, and a hedging method for economies with high inflation. Kılıç and Çütcü (2018) remark that the formation of unique exchanges of cryptocurrencies and the increase in transaction volumes should raise doubts about the future of traditional investment instruments and stock markets. However, the cryptocurrency market still lacks market depth, maturity, transparency, and regulation. In addition, uncertainties such as the dispersion of information among cryptocurrency users influence decision-making mechanisms (Bouri, Gupta, & Roubaud, 2019).

Cryptocurrencies were not considered a threat to financial stability in the early years. The European Central Bank (2012) stated that cryptocurrencies would not threaten financial stability because they have limited links to the real economy, have low transaction volumes, and are not widely accepted by users. However, if we examine the price development of cryptocurrencies in recent years, we can observe a meteoric rise and subsequent fall (Enoksen et al., 2020; Makarov & Schoar, 2020). After the explosion of the Bitcoin price, discussions about the intrinsic or fundamental value of cryptocurrency intensified. While many experts claimed that Bitcoin was a fraud and that its value would eventually fall to zero, others believed that Bitcoin's growth and further proliferation would continue (Wheatley et al., 2019). In a pioneering study, Cheah and Fry (2015) find that the fundamental value of the speculative bubbles which exist in Bitcoin markets is zero. Similarly, many studies (Bouri, Shahzad, & Roubaud, 2019; Cagli, 2019; Chaim & Laurini, 2019; Cheung et al., 2015; Corbet et al., 2018; Fry, 2018; Fry & Cheah, 2016; Geuder et al., 2019; Gronwald, 2021; Holub & Johnson, 2019; Li et al., 2021; Shu & Zhu, 2020; Xiong et al., 2020) confirm the existence of speculative bubbles in various cryptocurrency markets. As a result, researchers argue that Bitcoin is more of a speculative investment instrument than a medium of exchange (Baur et al., 2018; Glaser et al., 2014; Yermack, 2013).

Apart from these studies, there are several research papers dealing with the link between cryptocurrencies and other financial assets. For example, Zeng et al. (2020) examine the connectedness between cryptocurrencies and conventional financial assets and find that the connectedness between Bitcoin and conventional assets is weak. Corbet et al. (2018) explore the connectedness between cryptocurrency and financial assets and conclude that crypto assets are relatively isolated from financial and economic assets. Hussain Shahzad et al. (2020) examine the safe-haven and hedge properties of gold and bitcoin for G7 countries' stock markets with data from 2010 to 2018 and find that Bitcoin has a safe-haven role and acts as a hedge against the equity market in Canada. Conlon et al. (2020) study the safe-haven property of

Bitcoin and Ethereum for 6 international stock markets (MSCI World, S&P 500, FTSE 100, FTSE MIB, IBEX, and CSI 300) for the period between 2019 and 2020, and reveal that both cryptocurrencies lack the safe-haven property. Bouri et al. (2017) investigate the hedging and safe-haven role of Bitcoin against major stock market indices, bonds, oil, gold, the general commodity index, and the dollar index for the period July 2011 to December 2015 and find that Bitcoin is a weak hedging instrument but plays a strong safe-haven role against Asian stocks.

Our main hypothesis is that the explosive price behaviors in the Bitcoin market significantly and adversely affect the variance of equity returns. To explore this hypothesis, we use the bubble detection test proposed by Phillips and Shi (2020) and GARCH (1,1) model.

This empirical research complements the existing literature in at least two major ways. Firstly, we employ a bubble detection test which is widely used by academic researchers and regulators as a warning device for detecting such episodes and thereby retaining stability in economy and financial markets. Secondly, we consider an extended sample period, covering several financial and geopolitical events as well as before, during, and after the period of the COVID-19 pandemic spanning July 2010 to December 2022, providing a deeper understanding of how speculative bubbles affect the variance of stock index returns. No other recently published paper systematically addresses speculative bubbles in the Bitcoin market or measures their effects directly on the volatility of major stock indices. This ambiguity encourages us to establish a link between cryptocurrency and stock markets. We consider that this makes a significant contribution to the literature.

We investigate the effect of explosive price behaviors in the Bitcoin market on 10 major stock markets over a sample period between 2010 and 2022 at a daily frequency taking two econometric approaches. The results of the bubble detection procedure provide evidence of multiple bubble episodes, which originate during the expansionary monetary policy implementations of the leading central banks. Then we address the question of whether the explosive behaviors detected affect the variance of equity returns by employing a GARCH-GED model. We find that the existence of bubbles adversely affects the return variance at the conventional levels of significance. The volatility of returns strengthens after the termination of bubble episodes and this result is robust to using a larger window length.

Following the introduction, the second section provides a brief review of the data and methodology, the third presents the empirical results, and the last section presents our conclusions.

Data and Methodology

We use daily adjusted closing prices of the 10 largest stock markets in terms of market capitalization. The dataset, downloaded from Yahoo Finance, includes DJIA, NSQ, SSE, N225, HSI, SZSE, AEX, LSE, TSX, and BSE and spans July 21, 2010 to December 9, 2022, with a total of 2,517 daily observations. We select stock indices from the largest markets, including developed and emerging markets, for an appropriate representation of data. Daily logarithmic returns are calculated by taking the difference in the logarithms of two consecutive prices, plotted in Figure 1. We present summary statistics for each return in Table 2.

We follow Phillips and Shi (2020) (PS hereafter) and define a bubble as an explosive behavior of an asset price, representing exuberance in the speculative behavior driving the market. This definition identifies bubbles by their time series characteristics, as the price of an asset follows a mildly explosive or random-drift martingale process, as opposed to the martingale behavior observed during normal market conditions.

To date-stamp bubbles, we use the real-time bubble detection method proposed by PS, which has the advantage of overcoming both unconditional heteroscedasticity and the multiplicity problems encountered in other bubble identification procedures. This procedure is used by central bank economists, policymakers, and financial industry professionals.

The recursive ADF regression is given as:

$$\Delta y_t = \hat{\alpha}_{r_1,r_2} + \hat{\beta}_{r_1,r_2} y_{t-1} + \sum_{i=1}^{k} \hat{\psi}^{i}_{r_1,r_2} \Delta y_{t-i} + \hat{\varepsilon}_t \qquad (1)$$

where k is the (transient) lag order, r_1 and r_2 represent the start and endpoints of the total sample window in the regression.

Phillips et al. (2015) define GSADF as the largest ADF statistic obtained as the result of a double recursion in the range r_1 to r_2. In other words, the test is based on repeating the ADF regression in equation (1) for subsamples.

$$GSADF\ (r_0) = \sup_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2, r_0]}} \left\{ ADF^{r_2}_{r_1} \right\}. \qquad (2)$$

where

r_0, the smallest sample window,

r_1, the starting point of the sample sequence,

r_2, the endpoint of each sample.

The BSADF test determines the start and end dates of the bubbles during the sample period.

$$BSADF_{r_2}\ (r_0) = \sup_{r_1 \in [0, r_2, r_0]} \left\{ ADF^{r_2}_{r_1} \right\} \qquad (3)$$

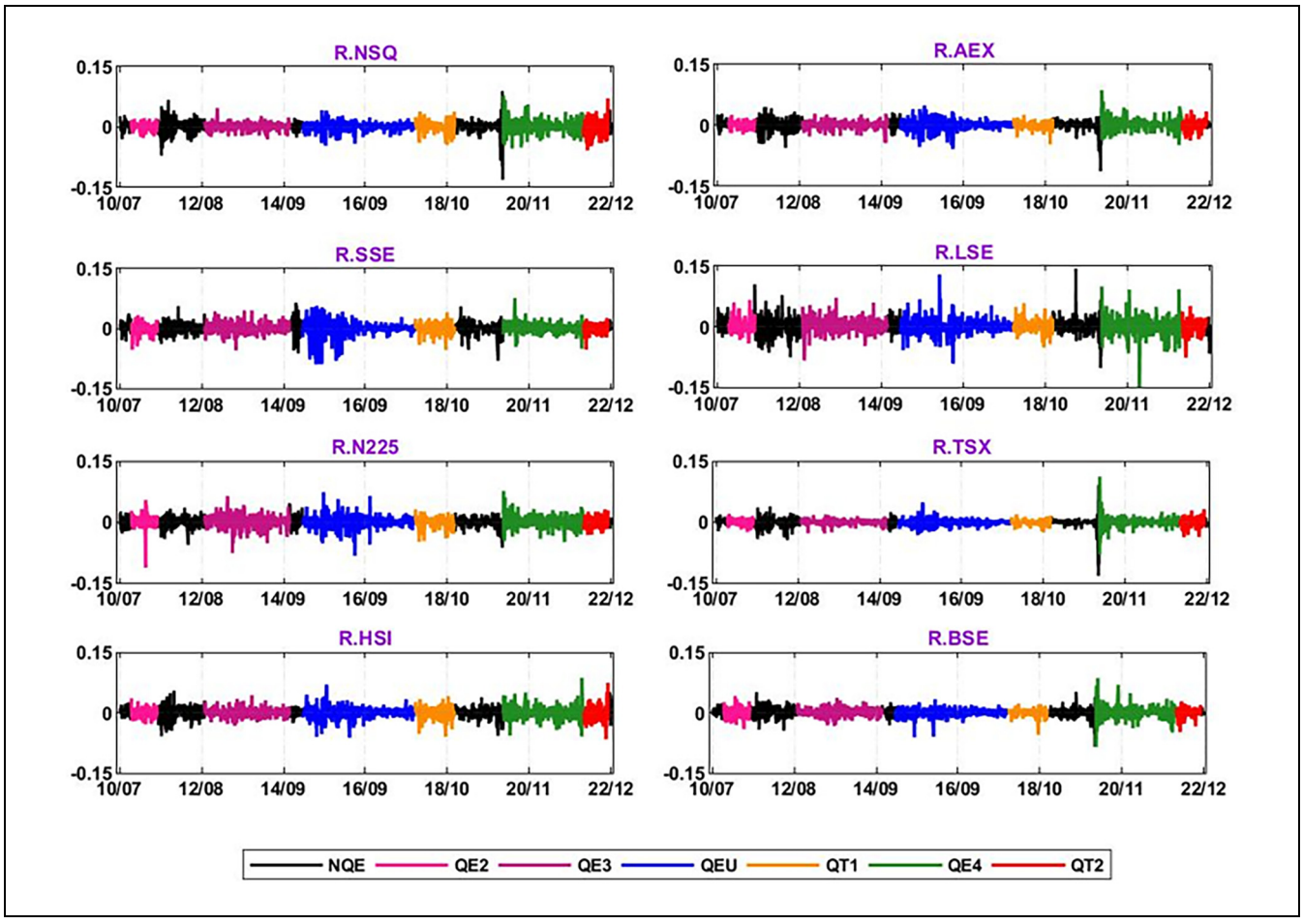


Figure 1. Index returns.
Note. NQE = non-quantitative easing periods; QE = quantitative easing launched by FED; QEU = quantitative easing launched by European Central Bank; QT = tapering schedule launched by FED.

The start and end date-stamps of the bubbles are estimated as:

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \left\{ r_2 : BSADF_{r_2}(r_0) > cv_{r_2}^{\beta_{T_{r_2}}} \right\}, \quad (4)$$

$$\hat{r}_f = \inf_{r_2 \in [r_e, 1]} \left\{ r_2 : BSADF_{r_2}(r_0) < cv_{r_2}^{\beta_{T_{r_2}}} \right\}, \quad (5)$$

where $cv_{r_2}^{\beta_T}$ shows the 100% (1-βT) critical value of the BSADF statistic for the number of observations r_2 in the full sample (T).

In the case of the existence of explosive price behaviors, we add dummy variables to the variance equation to determine the impact of these bubble periods on stock markets. Together, we test for structural breaks that might result from the dynamics of the stock markets themselves. Explosiveness in Bitcoin prices and breakpoints in equity markets could lead to unreliable results if they coincide. To detect discrete changes in the variance of a stock return series using the GARCH (1,1) model, the ICSS algorithm proposed by Inclán and Tiao (1994) computes the test statistic as:

$$IT = \sqrt{T/2}D_k, \quad (6)$$

where

$$D_k = (C_k/C_T) - (k/T), \quad k = 1, 2, 3 \ldots, T \quad D_0 = D_T = 0 \quad (7)$$

A series of uncorrelated random variables having a mean of 0 and a variance of σ_t^2, $t = 1, 2, 3 \ldots, T$, provide the basis of the expression $C_k = \sum_{t=1}^{k} \varepsilon_t^2$. According to Nikmanesh and Nor (2019), one of the criticisms of this testing method is that it assumes that the random series distribution is independent and homogeneous. When the series contains conditional variance elements, the test method proposed by Inclán and Tiao (1994) finds that the number of breaks is larger than it should be (Sansó et al., 2004). Therefore, they develop a test that modifies

the series to include the conditional variance feature. According to Monte Carlo simulation experiments, the updated test statistic produces better results.

Sansó et al. (2004) also use the iteration approach developed by Inclán and Tiao (1994) in their search for breakpoints in variance. They describe Kappa-1 (K1) and Kappa-2 (K2) as the adjusted test statistics for the distributional and conditional variance characteristics of the underlying series. The K1 test statistic, which shows that the series is not normally distributed and there is no ARCH effect, is defined as:

$$K_1 = \sup_k \left| T^{-1/2} B_k \right|, \tag{8}$$

where

$$B_k = \{C_k - k/TC_T\} / \sqrt{\hat{\eta}_4 \hat{\sigma}^4}; \tag{9}$$

$$\hat{\eta}^4 = T^{-1} \sum_{t=1}^{T} \varepsilon_t^4; \text{and} \hat{\sigma}^2 = T^{-1} C_t$$

If the series is not normally distributed but has the ARCH effect, the K2 test statistic is derived as:

$$K_2 = \sup_k \left| T^{-1/2} G_k \right|, \tag{10}$$

where $G_k = \hat{\omega}_4^{-1/2}(C_k - k/TC_T)$ and $C_k = \sum_{t=1}^{k} r_t^2$ are the sequence of uncorrelated random variables (squared after cumulative sum), with a mean of 0 and a variance σ_t^2 used in this example.

$\hat{\omega}_4$ is a consistent estimator of ω_4 calculated as:

$$\hat{\omega}_4 = 1/T \sum_{t=1}^{T} \left(a_t^2 - \hat{\sigma}^2\right)^2 + 2/T \sum_{t=1}^{m} \left(a_t^2 - \hat{\sigma}^2\right)\left(a_{t-1}^2 - \hat{\sigma}^2\right), \tag{11}$$

where $\omega(l, m)$ is defined as $\omega(l, m) = 1 - l/(m + 1)$, and x represents either a lag window or a quadratic spectral.

Empirical Results

The empirical results section is organized into two parts. Firstly, we describe the variables, present the summary statistics and visualize the return series, then discuss the bubble detection findings and the real-time bubble detection tests. Secondly, we address the impact of bubble formations on stock markets using the GARCH (1,1) model.

The results presented in Table 2 (Panel A) show that all stock returns are, on average, positive, except the R.HSI index, but close to zero over the sample period at a daily frequency. The R.LSE index exhibits the highest (14.27%) and lowest (−15.52%) daily changes and is also more volatile (0.0187) than the others, followed by R.SZSE (0.0175) and R.SSE (0.0144) in terms of standard deviation. None of the indices returns follow a normal distribution, as suggested by significantly negative/positive skewness, significantly positive excess kurtosis values, and the JB normality test statistics at the 99% confidence level. The probability values for the Ljung-Box test for returns, Q (20), and squared returns Q^2 (20), show a rejection of the null hypothesis, given that they are smaller than 0.05, and indicate that the residuals are not independently distributed, that is they exhibit serial correlation at predetermined lag 20. Moreover, the Engle's ARCH test probability values signify the existence of conditional heteroskedasticity (ARCH effects) and indicate the presence of volatility clustering or mean reversion in return series (see Figure 1). All returns series are stationary at the conventional significance level (Dickey and Fuller, 1979; ADF, hereafter; Phillips and Perron, 1988; PP, hereafter) and significantly positively correlated (Panel B) (Table 1).

GSADF Bubble Detection Test Results

Following the suggestions of Phillips et al. (2015) (PSY, hereafter) and Phillips and Shi (2020), we employ the GSADF test to the Bitcoin market as a first stage and present test statistics along with the critical values obtained using the wild bootstrap procedure execution of Harvey et al. (2016) with 2,000 replications in Table 2. Given that the test statistics for both lengths of window exceed the critical value at 5% significance, we strongly reject the null hypothesis of the nonexistence of bubble behavior in Bitcoin prices. The results provide evidence of multiple episodes of explosive behavior, in line with previous studies such as Gemici (2020), Anyfantaki et al. (2021), Diniz et al. (2022), and Gök (2022). Then we use the real-time bubble detection method, which is immune to unconditional heteroskedasticity and multiplicity problems, to date-stamp bubbles. The results for two minimum window size, 115 and 165, defined based on the rule $r_0 = 0.01 + 1.8/\sqrt{T}$, are depicted in Figure 2 and provided in Table 3.

In Figure 2, we illustrate the BSADF sequence (black solid line, left axis) and its critical values for a 95% confidence level (red dashed line, left axis) based on wild bootstrap simulations along with the time evolution of the underlying series (blue solid line, right axis). Note that we impose a minimum duration of 8 days, which is greater than the minimum duration achieved by the rule of thumb $\log(T) = 7.83$ (Phillips et al., 2015). In the top panel, some major financial, economic, pandemic, and

Table 1. Descriptive Statistics and Correlation Coefficients of Return Series.

	R.DJIA	R.NSQ	R.SSE	R.N225	R.HSI	R.SZSE	R.AEX	R.LSE	R.TSX	R.BSE
Panel A: Summary statistics										
Mean	0.0005	0.0007	0.0001	0.0005	−0.0001	0.0001	0.0004	0.0011	0.0003	0.0005
Median	0.0008	0.0013	0.0005	0.0007	0.0004	0.0003	0.0008	0.0008	0.0008	0.0007
Max	0.1077	0.0894	0.0755	0.0774	0.087	0.0723	0.086	0.1428	0.113	0.086
Min	−0.1385	−0.1315	−0.0891	−0.1116	−0.0657	−0.1039	−0.1138	−0.1553	−0.1318	−0.0854
SD	0.0118	0.0141	0.0144	0.0143	0.0137	0.0175	0.0123	0.0187	0.0104	0.0118
Skewness	−1.0228	−0.6373	−0.7615	−0.3334	−0.0396	−0.6017	−0.6037	0.0709	−1.4653	−0.4403
	0	0	0	0.0001	0.4165	0	0	0.1464	0	0
Kurtosis	19.0215	7.9224	6.1551	4.5519	3.4609	3.6723	6.9073	6.9924	31.526	7.0153
	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
JB	38368.9	6750.1	4214.8	2218.8	1256.4	1565.6	5154.5	5127.7	105092.9	5240.6
	0	0	0	0	0	0	0	0	0	0
Q (20)	597.3	272.4	124.5	89.1	72.1	101.3	83.6	136.5	381.4	156.8
	0	0	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0	0
Q^2 (20)	7600.3	5123.2	2033.9	833.4	927.4	2071.5	2685.6	498.3	8218.8	3666.4
	0	0	0	0	0	0	0	0	0	0
ARCH(20)	7237	4832	1522	799.2	824.8	1667	2490	496.9	8129	3154
	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
n	2516	2516	2516	2516	2516	2516	2516	2516	2516	2516
ADF	−24.898*	−30.817*	−49.05*	−51.408*	−49.194*	−48.655*	−48.429*	−49.928*	−22.795*	−49.648*
PP	−56.984*	−55.361*	−49.061*	−51.413*	−49.185*	−48.7*	−48.401*	−50.059*	−53.856*	−49.696*
Panel B: Correlation estimations										
R.DJIA	1									
R.NSQ	0.860*	1								
R.SSE	0.147*	0.168*	1							
R.N225	0.244*	0.217*	0.297*	1						
R.HSI	0.252*	0.268*	0.560*	0.515*	1					
R.SZSE	0.131*	0.157*	0.926*	0.262*	0.515*	1				
R.AEX	0.634*	0.589*	0.204*	0.393*	0.436*	0.187*	1			
R.LSE	0.348*	0.369*	0.133*	0.224*	0.264*	0.132*	0.534*	1		
R.TSX	0.801*	0.742*	0.188*	0.280*	0.329*	0.176*	0.646*	0.367*	1	
R.BSE	0.372*	0.327*	0.247*	0.359*	0.483*	0.233*	0.468*	0.271*	0.430*	1

*<.01.

Table 2. GSADF Test Results.

	Window length = 115 days				Window length = 165 days			
	Test statistic	10%	5%	1%	Test statistic	10%	5%	1%
BTC Prices	25.99**	16.7238	20.2607	26.7403	25.99**	17.2407	19.9447	26.5706

**Denotes rejection of the null hypothesis at the 95% confidence level. The test statistics and critical values are obtained by using two R packages of "psymonitor" by Caspi et al. (2018) and "exuber" provided by Vasilopoulos et al. (2018). To remedy the multiplicity issue in the recursive procedure, the empirical size is controlled over 35 days by taking tb = swindow0 + 35 − 1 = 149 (199) observations for each bootstrapped sample in the case of swindow0 = 115 (165) days. The number of lags is selected using BIC.

geopolitical events are shaded in the upper section, while the quantitative easing and tapering periods are shaded in the lower section. In the middle and lower panels, the identified origination and termination dates of bubble episodes lasting at least eight days are visualized, with each bubble period shaded green. Discarding exuberance periods shorter than 8 days reveals seven long-lived (at least 22 days) and four short-lived bubble periods for a window length of 115. Visual inspection suggests that the origination and termination dates of all bubble episodes match the monetary policy actions of the FED and ECB (quantitative easing and tapering), indicating that the cryptocurrency market is among the financial markets to benefit from cheap money, largely driven by the exuberance behavior of investors and great interest from major financial institutions. The test detects three long-lived

Table 3. Explosive Periods in Bitcoin Prices at Two Window Lengths.

Window length = 115 days (411 days)			Window length = 165 days (409 days)		
Starting date	Ending date	Duration	Starting date	Ending date	Duration
2011-04-26	2011-06-13	26	2011-05-18	2011-06-15	18
2012-08-02	2012-08-17	10	2012-08-02	2012-08-16	9
2013-01-22	2013-04-10	45	2013-01-18	2013-04-10	46
2013-10-31	2013-12-13	29	2013-10-28	2013-12-13	32
2017-02-21	2017-03-09	12	2017-02-21	2017-03-09	12
2017-04-26	2017-09-13	83	2017-04-24	2018-01-22	161
2017-09-15	2018-01-19	74			
2019-06-17	2019-06-28	10			
2020-12-16	2021-05-20	86	2020-12-14	2021-05-20	88
2021-08-20	2021-09-03	10	2021-08-20	2021-09-07	11
2021-10-08	2021-11-24	26	2021-10-08	2021-12-03	32

Gray-shaded areas represent a short-lived explosive period (<20 days).

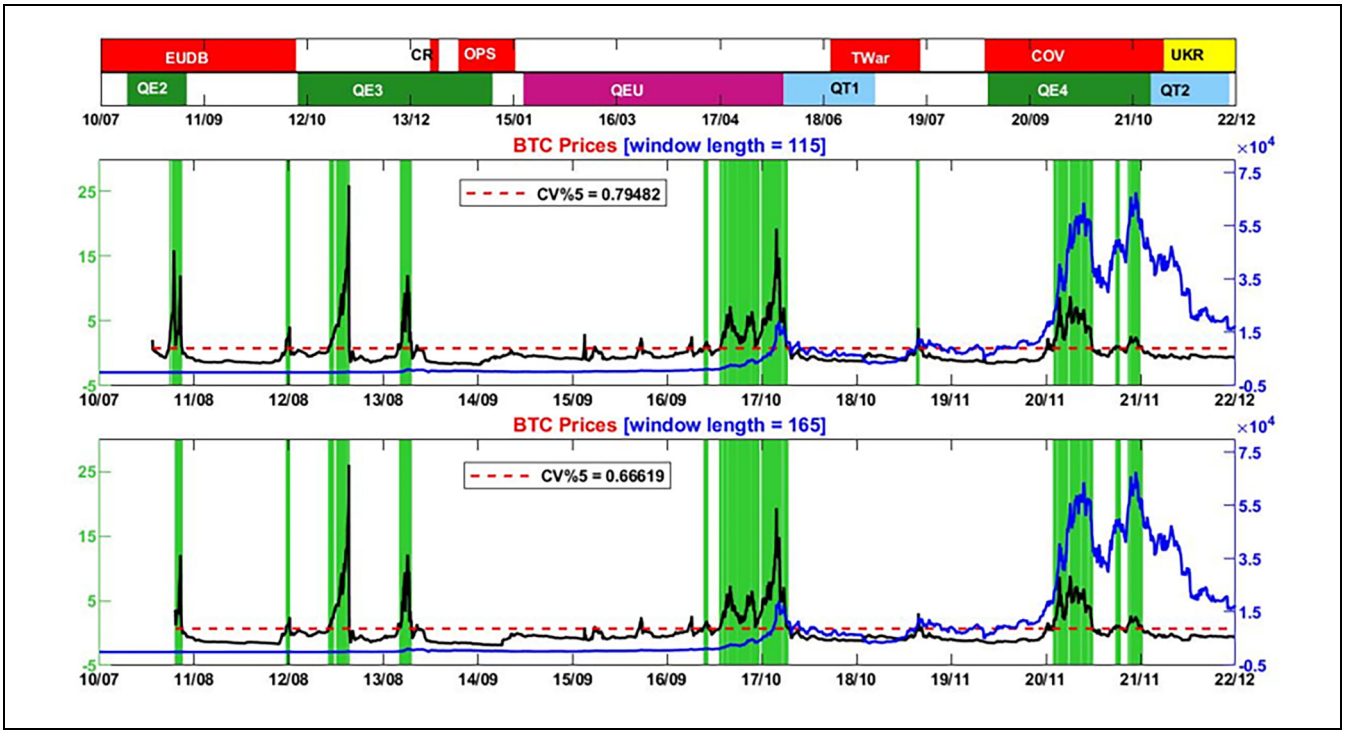


Figure 2. Bubble detection test results for Bitcoin prices for window length of 115 days (upper) and 165 days (bottom) panel.
Note. EUDB = Eurozone debt crisis; CR = the annexation of Crimea by Russia; OPS = oil price shocks; TWar = trade war between China and the US; COV = COVID-19 period; UKR = the invasion of Ukraine by Russia; QE = quantitative easing schedule launched by FED; QEU = quantitative easing launched by European Central Bank; QT = tapering schedule launched by FED (see upper panel). The GSADF test results with a window length of 115 and 165 days, highlighted with green-shaded areas (see the intermediate and bottom panels).

and one short-lived period of exuberance, ranging from 10 to 45 days, before 2014 when Bitcoin prices increased from $1.04 (February 2011) to $804.83 (December 2013). In 2013, we observe two positive mildly explosive episodes with different durations, which can be ascribed to the publication of the regulation on personal management of virtual currency in the United States, leading to the recognition of Bitcoin as a virtual currency and a

surge in the price. The second bubble lasting 29 days originates on October 31 and terminates on December 13, 2013, with the bad news of hundreds of thousands of missing Bitcoins at Mt. Gox, an exchange based in Japan that ceased operation in 2014. Li et al. (2021) and Diniz et al. (2022) among many others identify this period as an exuberance period. We observe one short-lived and two positive mildly long-lived explosive episodes, of which the second was a long-lasting episode of 83 days duration in 2017 and early 2018, with up to 10-fold price increases from $1,115.30 to $11,607.40. These explosive episodes are mostly in line with Bouri et al. (2019), Enoksen et al. (2020), Maouchi et al. (2022), and Gök (2022), coinciding with the last months of the quantitative easing schedule of ECB and tightening monetary policy settings of FED (QT1) in 2018. The Bitcoin market sees a short-lived period of price explosion, lasting 10 days, in June 2019 and the origination and termination dates of the bubble, respectively, could be ascribed to: (i) the release of a new currency payment business model "Libra" by Facebook, encouraging market confidence of Bitcoin; and (ii) the criticisms and suspicions of authorities concerning national security, monetary policy, privacy, and trading (Li et al., 2021). The longest-lived explosive episode, beginning in mid-December 2020, lasts 86 days, with the market posting a 91.3% increase in May 2021. As noted by Maouchi et al. (2022), this explosiveness might be driven by the announcement of major companies and institutional investors' involvement in investing or using cryptocurrencies. However, the burst in May 2021 coincided with bad news from Tesla and China. Tesla announced that it would no longer accept Bitcoin as payment currency for cars, while China banned financial institutions from the cryptocurrency business and warned investors against speculative activities in the market. Three months later, a short-lived explosive period originates and then terminates in September 2021. We date a positive and final mildly explosive period to the fourth quarter of 2021, which originates with the establishment of the first Bitcoin ETF in the United States and eventually bursts 26 days later to $53,967.85 from the highest value of $67,566.83 during this period.

It is quite evident that the results of the bubble detection test are similar and robust to a longer window of 165 days, as the total number of days with explosive prices for this specification is 409 (9 periods) compared to 411 (11 periods) for the specification with the minimum window size (see Table 3).

Estimating GARCH models

In this section, the GARCH (1,1) model is used to examine the impact of bubbles in Bitcoin prices on the variance of stock market index returns. However, due to the impact of numerous financial and economic crises that occurred during the period covered by the study, there may be structural breaks in the variance of the indices' return series. Therefore, these structural breaks need to be revealed to account for the impact of Bitcoin bubbles on the variance of stock index returns, because the volatility parameters in the GARCH model, which are estimated without taking structural breaks into account, turn out to be larger than they should be. To this end, the test developed by Inclán and Tiao (1994) and Sansó et al. (2004) is used to investigate whether there is a structural change in the variance of the index return series, and the results are presented in Table 4.

Table 4 shows the Inclán and Tiao (1994) and Sanso et al. (2004) test results. The results of Inclán and Tiao's (1994) test indicate that there are multiple breakpoints for each return series. However, this test tends to overestimate the breakpoints in the variance if the current series of returns are normally distributed and there is no ARCH effect. Therefore, we use the modified test results developed by Sanso et al. (2004). In this test, the Kappa-1 test is used when the series is not normally distributed and there is no ARCH effect, while the Kappa-2 test is used when the series is both not normally distributed and the ARCH effect is present. Therefore, we consider the result of the Kappa-2 test. Based on the results, a dummy variable is constructed to represent the breakpoints in the indices and Bitcoin bubble periods in the variance equation of the *GARCH (1,1)* model. In this way, the effects of structural breaks in the variance are eliminated from the model. By doing so, we determine which breakpoints in the variance equation are statistically significant.

The alpha (α) and beta (β) parameters in Table 5 and Table 6 are positive and their sums are less than one. This shows that the variance is stationary and the persistence of volatility has a high value. We use the GED distribution, which has the best error distribution because the indices' return series do not have normal distributions.

Tables 5 and 6 show the estimation results of the GARCH models for window lengths of 115 and 165 days, respectively. Note that the values in parentheses are the *p*-values of the estimates. The results in both tables show that explosive behaviors in the Bitcoin market, which are detected using the procedure of Philips and Shi (2020) and represented as a dummy variable (D), exhibit a significantly negative impact on the return variance of the stock markets, except for the three indices NSQ, HIS, and TSX. The monetary policy decisions of the FED and ECB, especially the quantitative easing programs, and the fact that traders trading on exchanges for speculative purposes turn to cryptocurrency markets

Table 4. Structural Breaks in Variance Test Results.

Index	Tests	Number of breaks	Number of observations corresponding to the break periods															
DJIA	Inclán and Tiao	21	210	288	711	756	847	950	1034	1055	1122	1274	1531	1541	1583	1671	1721	1948
			1975	2028	2058	2102	2341											
	Kappa-1	16	210	245	275	1033	1055	1136	1274	1531	1563	1613	1671	1721	1948	1976	2102	2341
	Kappa-2	0																
NSQ	Inclán and Tiao	18	207	275	498	1034	1055	1208	1534	1568	1670	1721	1839	1861	1948	1976	2009	2203
			2275	2358														
	Kappa-1	16	207	275	498	1034	1055	1208	1534	1568	1670	1721	1839	1861	1948	1976	2203	2275
	Kappa-2	1	2327															
SSE	Inclán and Tiao	22	674	766	812	878	911	966	1103	1120	1132	1137	1230	1536	1850	1935	1937	1968
			2020	2022	2037	2175	2358	2389										
	Kappa-1	6	674	878	1137	1230	1536	2389										
	Kappa-2	5	674	878	1230	1536	2037											
N225	Inclán and Tiao	16	128	136	492	638	756	851	867	1035	1055	1274	1531	1565	1663	1722	1948	1975
	Kappa-1	5	1035	1274	1936	1957	1975											
	Kappa-2	1	1516															
SZSE	Inclán and Tiao	11	878	994	1103	1120	1163	1230	1533	1738	1807	1935	1968					
	Kappa-1	7	610	877	994	1050	1163	1533	2037									
	Kappa-2	4	610	877	1230	1533												
BSE	Inclán and Tiao	18	548	655	892	1201	1319	1534	1567	1660	1687	1868	1871	1933	1957	1982	2192	2278
			2346	2418														
	Kappa-1	5	378	1660	1959	1975	2418											
	Kappa-2	3	378	1201	1660													
HSI	Inclán and Tiao	19	213	276	674	951	1036	1055	1201	1276	1456	1536	1568	1663	1707	1933	2035	2070
			2363	2367	2486													
	Kappa-1	10	213	281	674	951	1201	1536	1707	1933	2022	2336						
	Kappa-2	1	2336															
AEX	Inclán and Tiao	19	210	275	417	547	600	851	859	1028	1055	1136	1191	1209	1291	1534	1948	1982
			2093	2302	2427													
	Kappa-1	13	210	275	417	851	1028	1209	1291	1534	1948	1982	2093	2302	2427			
	Kappa-2	0																
LSE	Inclán and Tiao	14	190	266	608	878	1130	1136	1191	1396	1527	1567	1667	1679	1837	1844		
	Kappa-1	7	190	371	1092	1209	1322	1527	1837									
	Kappa-2	2	1209	1837														
TSX	Inclán and Tiao	25	207	275	417	471	474	548	563	630	719	844	919	1033	1055	1105	1127	1407
			1530	1561	1669	1725	1939	1948	1982	2010	2384							
	Kappa-1	20	207	275	417	548	630	719	844	919	1033	1055	1105	1127	1347	1669	1725	1948
			1982	2198	2275	2384												
	Kappa-2	0																

Table 5 GARCH (1,1) Model for Bubble Periods Using a 115-Day Window.

	DJIA	NSQ	SSE	N225	SZSE	BSE	HSI	AEX	LSE	TSX
ω	0.0498	0.3920	0.0398	0.0943	0.0683	0.0360	0.1862	0.0623	1.3335	0.0232
	(0.0000)	(0.0178)	(0.0002)	(0.0001)	(0.0004)	(0.0000)	(0.0164)	(0.0000)	(0.0000)	(0.0000)
α	0.1567	0.1346	0.0592	0.1004	0.0564	0.0766	0.0549	0.1245	0.1709	0.1277
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.8080	0.8241	0.9181	0.8560	0.9193	0.8984	0.9189	0.8371	0.5386	0.8481
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D	−0.0231	−0.0191	−0.0267	−0.0384	−0.0374	−0.0164	−0.0151	−0.0270	−0.1918	−0.0067
	(0.0101)	(0.1279)	(0.0041)	(0.0351)	(0.0207)	(0.0660)	(0.1643)	(0.0378)	(0.0212)	(0.1786)
V1		−0.3238	0.0245		0.0315		−0.1414		−0.2373	
		(0.0431)	(0.0503)		(0.0872)		(0.0441)		(0.0824)	
V2									−0.8099	
									(0.0000)	
G	1.1700	1.2144	1.1022	1.2437	1.1893	1.3184	1.2322	1.2062	1.1309	1.2498
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α + β	0.9647	0.9587	0.9773	0.9564	0.9757	0.9750	0.9738	0.9616	0.7095	0.9758
Ln(L)	−3244.62	−3850.99	−3989.87	−4153.61	−4632.83	−3626.93	−4065.74	−3642.15	−4785.66	−2855.68
Q(50)	51.053	43.158	33.625	42.182	34.221	60.795	57.893	50.574	48.595	56.059
	(0.160)	(0.338)	(0.818)	(0.550)	(0.855)	(0.071)	(0.078)	(0.145)	(0.165)	(0.038)
Qs(50)	41.897	29.731	30.923	45.057	26.004	38.682	49.172	58.794	14.223	92.457
	(0.786)	(0.990)	(0.984)	(0.672)	(0.998)	(0.877)	(0.507)	(0.185)	(1.000)	(0.000)

Note. Values in parentheses are probability values. V1 and V2 are structural breaks dummies in the variance. *Q*(50) and *Qs*(50) show the results of the Ljung-Box autocorrelation test for the returns and the squares of returns, respectively. G = generalized error distribution (GED); Ln(L) = the highest likelihood value of the model; D = dummy variable for Bitcoin bubble periods.

Table 6. GARCH (1,1) Model for Bubble Periods in the 165-Day Window.

	DJIA	NSQ	SSE	N225	SZSE	BSE	HSI	AEX	LSE	TSX
ω	0.0498	0.0682	0.0398	0.0951	0.0679	0.0352	0.1747	0.0862	1.0968	0.0248
	(0.0000)	(0.0000)	(0.0002)	(0.0001)	(0.0004)	(0.0008)	(0.0184)	(0.0000)	(0.0000)	(0.0000)
α	0.1567	0.1349	0.0592	0.1012	0.0563	0.0761	0.0550	0.1246	0.1702	0.1269
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.8080	0.8238	0.9181	0.8545	0.9196	0.8993	0.9208	0.8370	0.5381	0.8468
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D	−0.0231	−0.0191	−0.0267	−0.0383	−0.0371	−0.0160	−0.0125	−0.0270	−0.1934	−0.0083
	(0.0101)	(0.1281)	(0.0041)	(0.0383)	(0.0210)	(0.0697)	(0.2249)	(0.0377)	(0.0199)	(0.1041)
V1		0.3243	0.0245		0.0312		−0.1332		−0.5720	
		(0.0432)	(0.0502)		(0.0886)		(0.0481)		(0.0002)	
V2									0.2462	
									(0.0715)	
G	1.1700	1.2148	1.1021	1.2434	1.189	1.3219	1.2211	1.2062	1.1353	1.2288
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α + β	0.9647	0.9587	0.9773	0.9557	0.9759	0.9754	0.9616	0.9616	0.7083	0.9737
Ln(L)	−3244.62	−3851.00	−3989.87	−4150.35	−4632.83	−3630.69	−4054.57	−3642.15	−4786.8	−2846.65
Q(50)	51.053	42.858	33.665	44.767	34.212	58.160	52.853	50.581	49.621	46.576
	(0.160)	(0.350)	(0.817)	(0.356)	(0.855)	(0.127)	(0.068)	(0.145)	(0.142)	(0.091)
Qs(50)	41.897	29.712	30.922	47.433	25.966	38.785	50.641	58.797	14.263	90.895
	(0.786)	(0.990)	(0.984)	(0.577)	(0.998)	(0.875)	(0.448)	(0.184)	(1.000)	(0.000)

Note. Values in parentheses are probability values, V1 and V2 are structural breaks dummies in the variance. *Q* (50) and *Qs* (50) show the results of the Ljung-Box autocorrelation test for the returns and the squares of the returns, respectively. G = generalized error distribution (GED); Ln(L) = the highest likelihood value of the model; D = dummy variable for bitcoin bubble periods.

during bubble episodes, may lead to a decline in the return variance of local exchanges. However, as is evident from Figures 3 and 4, the return variance of local stock markets rises during non-bubble periods. Notably, the empirical results of the conditional variance show that the price explosiveness in BTC affects

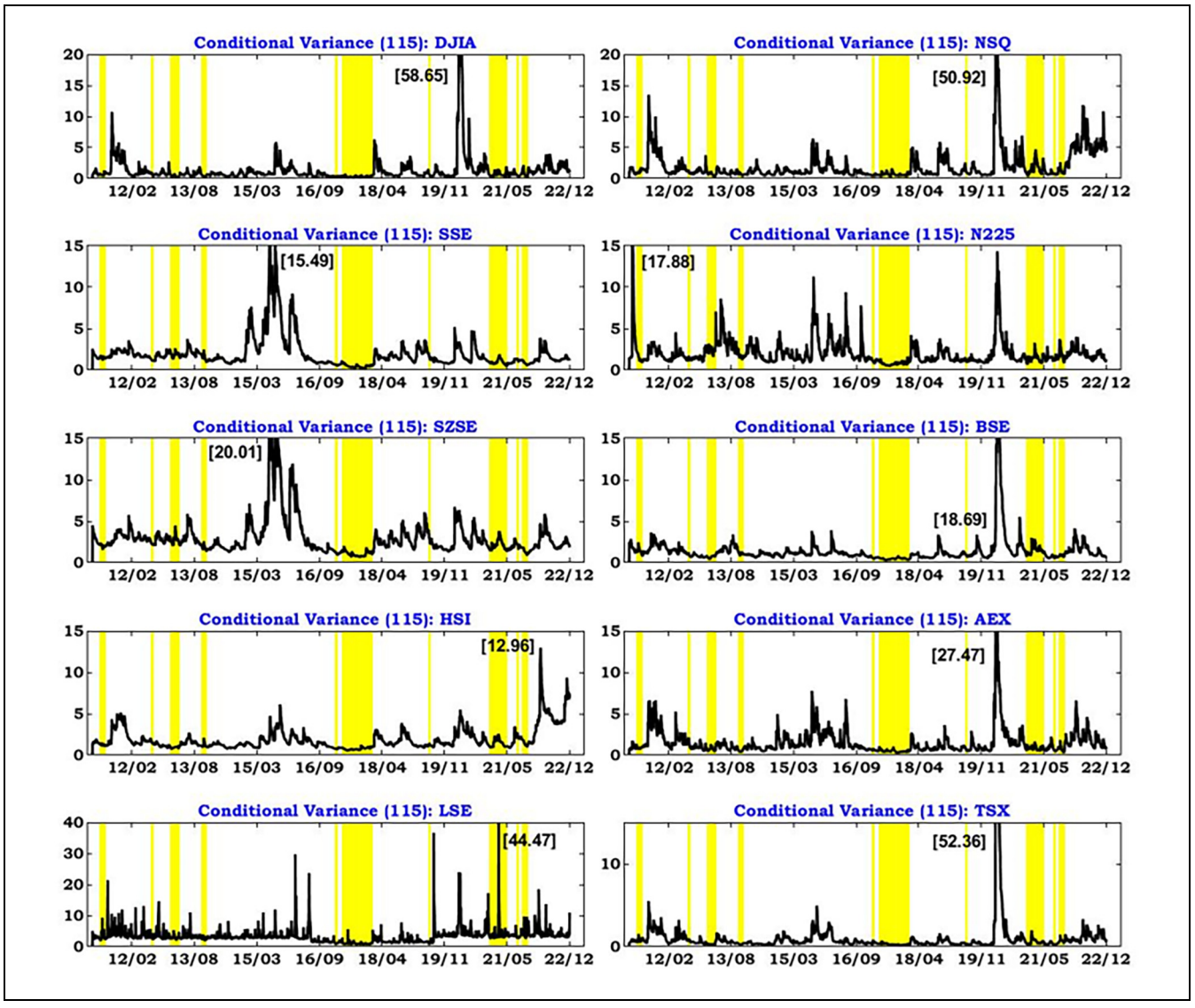


Figure 3. Conditional variance of index returns and bubble episodes for window length of 115 days.

the return variances of stock markets at varying significances and magnitudes. This result explicitly suggests that the impact is not related to the level of financial development of the financial market. In line with the findings of Umar et al. (2021), we conclude that investors should exit this market immediately to reduce portfolio losses and protect their assets in times of falling BTC.

Conclusion

We find explosive price behaviors in the Bitcoin market, then gauge their impact on major stock market indices over the sample period 2010 to 2022. The bubble detection test results show evidence of multiple short- and long-lived bubble episodes in the Bitcoin market, and their origination and termination dates markedly coincide with the acceptance or rejection of Bitcoin as a payment instrument in particular, and the implementation periods of expansionary monetary policies, particularly those implemented by the FED. To measure the impact of the exuberance and collapse in Bitcoin prices on the variance of equity returns, a GARCH (1,1) model comprising two dummy variables is implemented, with each explosive price behavior in Bitcoin as well as structural breaks identified in stock markets taking values of 0 or 1. The results show that the effect is significantly negative for most stock markets, suggesting that Bitcoin

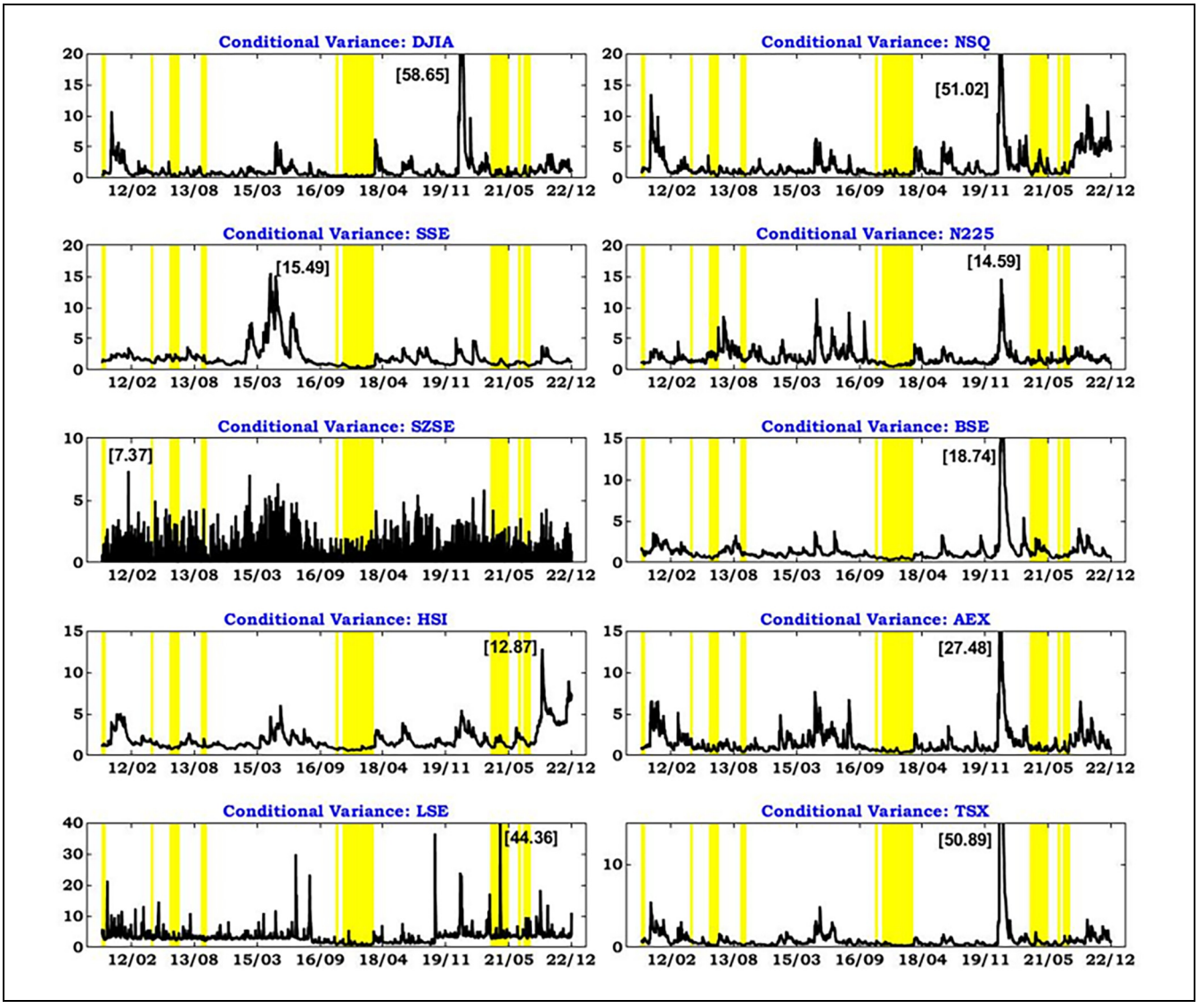


Figure 4. Conditional variance of index returns and bubble episodes for window length 165 days.

bubbles play a vital role in the return volatility of equities regardless of market capitalization.

These findings have important implications for decision-making by policymakers and investors. Firstly, our results suggest using the PS test as a real-time bubble detector to help policymakers maintain economic and financial stability, since this algorithm allows timely policy action and effective risk management to avoid or reduce serious real and financial damage (Phillips & Shi, 2020). Furthermore, investors can use our findings to explain volatility in stock markets during and after the bubble episodes in cryptocurrency markets given that bubble formation and collapse can drive volatility in stock returns and thereby lead to higher losses in portfolios. As suggested by Gök (2021), investors may behave rationally when they perceive the early signs of explosive price behaviors in the Bitcoin market and leave the market, being content with the profits obtained before the collapse and therefore providing protection against downside risk. Investigating the impacts of bubbles on the return volatility of stock markets with novel econometric approaches and considering the relative importance of other variables, such as policy uncertainty or geopolitical risk indicators, would be a fruitful area for future empirical studies.

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