Research Article

Time- and Quantile-Varying Causality between Investor Attention and Bitcoin Returns: A Rolling-Window Causality-in-Quantiles Approach

Jianqin Hang and Xu Zhang

1School of Economics and Management, Jiangsu Maritime Institute, Nanjing 211170, China
2School of Management Science and Engineering, Nanjing University of Information Science & Technology, Nanjing 210044, China
3Nanjing Institute of Digital Financial Industry, Nanjing 210018, China

Correspondence should be addressed to Jianqin Hang; hangjianqin_8788@126.com

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Abstract

This study proposes a novel approach that incorporates rolling-window estimation and a quantile causality test. Using this approach, Google Trends and Bitcoin price data are used to empirically investigate the time-varying quantile causality between investor attention and Bitcoin returns. The results show that the parameters of the causality tests are unstable during the sample period. The results also show strong evidence of quantile- and time-varying causality between investor attention and Bitcoin returns. Specifically, our results show that causality appears only in high volatility periods within the time domain, and causality presents various patterns across quantiles within the quantile domain.

1. Introduction

Cryptocurrencies, a new form of digital assets, have drawn the attention of investors, researchers, and central banks since the global financial crisis. Based on the blockchain technology, a large number of cryptocurrencies have been produced and traded since the introduction of the well-known Bitcoin in 2008. Despite some shortcomings, it is widely regarded that such decentralized and encrypted currencies will be a subversive asset that brings shocks to the financial system. Hence, it is critical for investors and supervisors to identify the price mechanism to manage risks better.

Due to their sharp volatility, cryptocurrency price movements have garnered much attention from economic scholars. Existing literature on cryptocurrency price movements includes two branches. The first focuses on the characteristics of cryptocurrency returns, including clusterings [1], explosivities [2], bubbles [3, 4], memories [5, 6], and herd effects [7, 8]. The second captures correlations among cryptocurrencies. For example, in their dynamic network analysis, Balli et al. [9] find that the short-term connectedness among cryptocurrencies is much stronger than medium and long term, and the connectedness decreases with the increase in economic uncertainty. Yi et al. [10] show that Bitcoin plays a key role in the connectedness network of cryptocurrencies. Related studies have been conducted by Fousekis and Tzaferi [11] and Katsiampa [12], among others.

In behavioral finance, the investor attention is considered an important behavior that affects asset returns. As the investors in financial markets have limited cognitive abilities [13–15], they are more inclined to trade these assets that catch their attention, implying that attention is a scarce resource. On the other hand, large fluctuations in asset prices attract more attention from investors and even cause a spiral between price fluctuations and investor attention, leading to greater fluctuations. Therefore, clarifying the price
mechanism through which price fluctuations and investor attention interact with each other conduces to better avoiding risks.

Prior studies have used several proxies to measure investor attention including trading volume [15], advertising expenses [16], media coverage [17], and price limits [18]. However, these proxies are indirect measures and based on the assumption that investors have paid attention to the news. To improve the effectiveness of proxy, Da et al. [19] use the Google search volume as a direct measure for investor attention. As Chen [20] describes, investor attention measured by Google search volume has an effect on stock returns. Similar studies include Lou [21], Vozlyublenaia [22], Welagedara et al. [23], and Adra and Barbopoulos [24], among others. Undoubtedly, Google search volume is a more convincing proxy for investor attention.

Due to the popularity of Google search volume, more and more scholars investigate the causal relationship between investor attention and cryptocurrencies returns using linear or nonlinear causality methods. The studies based on quantile causality method show evidence that the causality between investor attention and cryptocurrencies returns varies across quantiles. However, existing literature has ignored the possible time variation in the bidirectional causal relationship between investor attention and cryptocurrency returns. Structural changes caused by factors such as technology evolutions, financial crises, and large disasters may lead to changes in the causal relationship [25]. Recent studies provide strong evidence of time-varying causality among economic variables [26, 27].

Our study contributes to existing literature in two ways. First, we develop a rolling-window-based approach that is used to examine the time-varying quantile causality. Although there are several studies on the relationship between investor attention and Bitcoin returns, most of them ignore the possible causality variation in the time and quantile domains. Second, we provide some new empirical observations that can be used to better understand the relationship between investor attention and asset returns. The results show strong evidence that investor attention-asset return causality is time varying and significant in high volatility periods, and the causality presents various patterns across quantiles.

The remainder of this paper is structured as follows. Section 2 reviews theoretical and empirical literature. Section 3 outlines econometric methods. Section 4 describes the data. Section 5 provides the empirical results, and Section 6 concludes the paper.

2. Literature Review

2.1. Determinants of Cryptocurrencies Returns. Unlike other financial assets, cryptocurrencies prices have experienced a miracle of growth in the past decade. Thus, the determinants of cryptocurrencies returns have garnered much attention. These determinants can be divided into external and internal variables. The external variables include commodity prices [28], stock prices [29], political and economic uncertainty [30], and other economic variables [31]. For example, Rehman and Vo [28] document that the impacts of precious metals on cryptocurrencies returns change across investment periods and market conditions. Sovbetov [29] shows that cryptomarket-related factors and the SP500 index affect cryptocurrencies returns. Colon et al. [30] demonstrate that political and economic uncertainty drives cryptocurrency market returns, and the magnitude of the effects depends on the type of uncertainty. Kristoufek [31] uses a wavelet coherence method and finds that Bitcoin is affected by fundamental factors such as money supply and usage in trade.

The internal factors that affect cryptocurrencies returns include trading volume, realized volatility, and investor attention. For example, Fousekis and Grigoriadis [32] identify the predictability between returns and volume in cryptocurrency markets and find that only high-level trading volume tends to precede extreme positive returns. Using a VAR framework, Urquhart [33] investigates the determinants of investor attention in Bitcoin and finds that realized volatility and volume are the main driving factors of the next day’s attention in Bitcoin.

Except for trading volume and realized volatility, investor attention is viewed as a crucial internal variable that affects cryptocurrencies returns. Based on the LASSO framework, Panagiotidis et al. [34] find evidence that search intensity affects Bitcoin returns. Using the VAR model, Shen et al. [35] find that investor attention, measured by Twitter data, affects Bitcoin trading volume and volatility, and Kristoufek [36] shows evidence of close connection between attention and Bitcoin returns. Garcia and Schweitzer [37] identify that spikes in Google search precede drastic decline of Bitcoin price. Kim et al. [38] demonstrate that user comments and replies in cryptocurrency markets are associated with trading volume. Phillips and Gorse [39] use the wavelet coherence method to study the comovement between cryptocurrencies returns and its related factors and find that the correlations are significant during bubble-like regimes. Bleher and Dimpfl [40] evaluate the usefulness of Google search volume to predict returns and volatility of cryptocurrencies and find that the returns are not predictable while volatility is predictable. Using a VAR framework, Guindy [41] shows that investor attention is related to higher price volatility. In sum, the existing literature provides strong evidence of nonlinear correlation between cryptocurrencies returns and its determinants.

2.2. Causal Relationship between Investor Attention and Cryptocurrencies Returns. Currently, there is a growing interest in examining the causality between investor attention and cryptocurrencies returns using linear and nonlinear causality methods. For example, Zhu et al. [42] conduct a linear Granger causality test and find that investor attention Granger causes Bitcoin returns and realized volatility. Bejaoui et al. [43] test the linear causality between media attention and Bitcoin returns during the COVID-19 outbreak and find no evidence of causality between social media proxied by Tweets and Google Trends data and Bitcoin returns. Shen et al. [35] find that the number of tweets does not Granger cause cryptocurrencies returns by a
linear approach, whereas the causality holds according to a nonlinear Granger causality test. Zhang and Wang [44] use a linear causality approach to examine the relationship between investor attention and cryptocurrencies returns and find evidence of bidirectional Granger causality. In sum, these studies based on linear Granger causality methods have provided strong evidence of unidirectional or bidirectional causality between investor attention and cryptocurrencies returns.

Our study is closer to those of Li et al. [45], Li et al. [46], and Subramaniam and Chakraborty [47]. Using the wavelet-based quantile causality test, Li et al. [45] examine the quantile causal relationship between investor attention and cryptocurrency returns and find that there exists significant bidirectional causality for all cryptocurrencies and that the causality demonstrates asymmetric and varies across quantiles and cryptocurrencies. Li et al. [46] use a nonparametric wavelet-based causality approach to test the multiscale causality between attention and cryptocurrencies returns for 27 cryptocurrencies. Their results indicate bidirectional causality holds for most of the cryptocurrencies. Using quantile causality method, Subramaniam and Chakraborty [47] investigate the causal relationship between investor attention and cryptocurrency returns and find that Bitcoin and Ethereum returns cause investor attention at all quantiles and investor attention causes cryptocurrency prices during the period of high investor attention. Though these quantile-based causality studies have provided evidence that the causality between investor attention and cryptocurrencies returns varies across quantiles, most of them have ignored the possible time variation in the bidirectional causality.

3. Methodology

In recent years, quantile-related methods have been widely used in economics and management [27, 48–50]. Among them, the quantile causality test is a new methodology used to test the nonlinear causality between variables. Inspired by the idea of the rolling-window causality test developed by Kaewsompong et al. [51], we propose a novel methodology that incorporates the rolling-window estimation and quantile causality test developed by Nishiyama et al. [52], Jeong et al. [53], and Balciar et al. [54, 55].

In the first step, we denote \( x_t \) as the daily investor attention to Bitcoin and \( y_t \) as Bitcoin returns. However, in the second step, we denote \( y_t \) as the daily investor attention to Bitcoin and \( x_t \) as Bitcoin returns. Following Jeong et al. [53], the variable \( x_t \) causes \( y_t \) in the \( \tau \)th quantile (\( 0 < \tau < 1 \)) with respect to the information set of \( \{ y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p} \} \) if

\[
Q_t\{ y_{t|y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}} \} \neq Q_t\{ y_{t|y_{t-1}, \ldots, y_{t-p}} \}.
\]  

(Q1)

where \( Q_t\{ y_{t|\cdot} \} \) denotes the \( \tau \)th conditional quantile of \( y_t \) given the information set. \( x_t \) is a prima facie cause of \( y_t \) in the \( \tau \)th quantile (\( 0 < \tau < 1 \)) respect to the information set of \( \{ y_{t|y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}} \} \) if

\[
Q_t\{ y_{t|y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}} \} \neq Q_t\{ y_{t|y_{t-1}, \ldots, y_{t-p}} \}.
\]  

(2)

Following Jeong et al. [53], we denote, \( X_{t-1} = (x_{t-1}, \ldots, x_{t-p}) \), \( Y_{t-1} = (y_{t-1}, \ldots, y_{t-p}) \), and \( Z_t = y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p} \). Let \( F_{y|Z}(y_t|Z_t) \) be the conditional distribution function of \( y_t \) given \( Z_t \). Denote \( Q_t(Z_t) \equiv Q_t(y_t|Z_t) \) and \( Q_t(Y_{t-1}) \equiv Q_t(y_t|Y_{t-1}) \). we then have

\[
F_{y|Z}(y_t|Z_t) = \tau \text{ with a probability of 1}.
\]

Given the definitions above, the null hypothesis can be expressed as follows:

\[
H_0: P[F_{y|Z}(y_t|Z_t) = \tau] = 1,
\]  

(3)

\[
H_1: P[F_{y|Z}(y_t|Z_t) = \tau] < 1.
\]  

(4)

Jeong et al. [53] use the distance measure

\[
j = E[\epsilon_t E[\epsilon_t|Z_t] f_Z(Z_t)],
\]  

where \( \epsilon_t \) is the regression error and \( f_Z(Z_t) \) is the marginal density function of \( Z_t \) to test the null hypothesis (3). They provide a feasible kernel-based test statistic of \( j \), which has the following form:

\[
\tilde{j}_t = \frac{1}{T(T-1)h^m} \sum_{t=1}^{T} \sum_{s=t}^{T} K(\frac{Z_{t-1} - Z_{s-1}}{h}) \tilde{\epsilon}_t \tilde{\epsilon}_s,
\]  

(5)

where \( m = p + q \), and \( K() \) denotes the kernel function, where \( h \) is the bandwidth. The regression error \( \tilde{\epsilon}_t \) is estimated as

\[
\tilde{\epsilon}_t = I\{ y_t < Q_t(Y_{t-1}) \} - \tau,
\]  

where \( Q_t(Y_{t-1}) \) is an estimate of the \( \tau \)th conditional quantile of \( y_t \) given \( Y_{t-1} \) and \( \tilde{\epsilon}_t \) is estimated by a nonparametric kernel method, that is, \( \tilde{\epsilon}_t \equiv \tilde{\epsilon}_t(Y_{t-1}) \equiv \tilde{\epsilon}_t(y_t|Y_{t-1}) \) is the Nadaraya-Watson estimator given by

\[
\tilde{\epsilon}_t(y_t|Y_{t-1}) = \frac{\sum_{s=t}^{T} L((Y_{t-1} - Y_s)/h)}{\sum_{s=t}^{T} L((Y_{t-1} - Y_s)/h)} \left( y_t \leq y_s \right).
\]  

(6)

We use the test for the 2nd moment developed by Balciar et al. [54, 55], who extend the framework of Jeong et al. [53]. To conduct this test, we employ the nonparametric quantile-based causality method. To demonstrate the higher-order moments test, we assume that

\[
y_t = g(Y_{t-1}) + \sigma(x_{t-1}) + \epsilon_t,
\]  

(7)

where \( g() \) and \( \sigma() \) denote functions that satisfy conditions for stationarity. According to Balciar et al. [54, 55], the Granger causality-in-variance does not require an explicit specification of squares for \( X_{t-1} \). Hence, we rewrite equation (7) into a null and alternative hypothesis for testing causality-in-variance as

\[
H_0: P[F_{y^2|Z}(Q_t(Y_{t-1})|Z_t) = \tau] = 1,
\]  

(8)

\[
H_1: P[F_{y^2|Z}(Q_t(Y_{t-1})|Z_t) = \tau] < 1.
\]  

To test causality for the 2nd moment, Balciar et al. [54, 55] construct the following model:
Thus, the higher-order quantile causality test can be specified as

\[ H_0: P[F_{\tau|\tau_1}^{|y_i|}\{Q_{\tau}(Y_{t-1})|Z_{\tau_1}\} = \tau] = 1, \quad \text{for} \ k = 1, 2, \ldots, K, \]

\[ H_1: P[F_{\tau|\tau_1}^{|y_i|}\{Q_{\tau}(Y_{t-1})|Z_{\tau_1}\} = \tau] < 1, \quad \text{for} \ k = 1, 2, \ldots, K. \]

(10)

According to Balcilar et al. [54, 55], failure to reject the null of noncausality for \( k = 1 \) does not necessarily mean failure to reject the null for \( k = 1 \).

To perform the test, three key parameters need to be determined: the bandwidth \( h \), lag order \( p \), and kernel type for \( K(\cdot) \) and \( L(\cdot) \). We determine the lag order \( p \) according to the Schwarz information criterion under the VAR framework. The bandwidth \( h \) is set using the least-squares cross-validation method. Gaussian kernels are selected for \( K(\cdot) \) and \( L(\cdot) \).

Recent studies on causality among economic variables have provided strong evidence in favor of time-varying causality, suggesting the hypothesis that causality among variables is constant is not always satisfied. The assumption may be violated by structural changes caused by financial crises and technology revolutions, leading to time-varying causality. To avoid unreliable results caused by structural changes, we combine the rolling-window estimation and quantile causality test. Specifically, the time-varying quantile causality between investor attention and Bitcoin returns is examined by estimating the moving subsamples with a fixed size \( d \) from the beginning to the end of the sample by adding one observation from ahead and eliminating one from behind. Consequently, we can obtain the \( T - d \) test statistics for the causality test.

4. Data

This section describes the measures used and data sources. Our analysis is based on two variables: Bitcoin returns and the attention to Bitcoin, measured at daily frequency. The daily Bitcoin price index (BP) is obtained from the website https://data.bitcoinity.org. With respect to the investor attention (IA) to Bitcoin, there exist a number of measures, such as trading volume, media coverage, and price limits. Considering the effectiveness of measures, we use a direct way to measure investor attention, that is, Google search volume. Google search volume data are from Google Trends (http://trends.google.com). Google Trends is a Google tool that analyzes the popularity of top search queries in Google Search across various regions and languages. Specifically, we use the term “Bitcoin” as the search keyword. With respect to the search region, we select the term “global”. We selected “global” because Bitcoin investors are spread worldwide. Our sample period starts on July 5, 2011, when daily Google search data are available and extends to June 8, 2021. The sample contains 3,626 daily observations. All the variables are transformed into their natural logarithms.

Figures 1 and 2 present the time-series plots for the Bitcoin return and investor attention. From the figures, we observe that the peaks and valleys of Bitcoin price and search volume are synchronized, implying that they are highly correlated. Table 1 displays the descriptive statistics. As seen in Table 1, Bitcoin price and investor attention change significantly during the sample period. The average daily growth of IA (dIA) is 0.0011, which is much smaller than that of BP (dBp). However, the volatility of dBp, measured by standard deviations, is much larger than that of dIA. According to Skewness and Kurtosis statistics, we can conclude that both dIA and dBp subject to the fat-tailed distribution, and their skewness is precisely opposite. Taken in their entirety, investor attention and Bitcoin prices continue to rise consecutively and show high volatility over the past years.

5. Empirical Results

5.1. Unit Root Tests. To test the causality between investor attention and Bitcoin returns, we first perform some unit root tests, including the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. We perform the tests with both a constant and a constant and a time trend. Table 2 displays the results. According to the results of ADF tests, we fail to reject the null hypothesis of a unit root for the lnIA and lnBP series under all specifications, implying that these two series are nonstationary. However, we reject the null hypothesis for the dIA and dBp series, implying that these two series are stationary. Furthermore, the results of the KPSS tests are consistent with the ADF tests. These results suggest that the lnIA and lnBP series are I (1) processes. Therefore, we use the differences in the logarithms of IA and BP for empirical analyzes.

5.2. Parameter Stability Test. To determine whether to use a time-varying causality methodology, we perform a set of parameter stability tests. Specifically, we use Chow [56] and Bai and Perron [57] tests to check break points, and Broock et al.’s [58] BDS test to examine the nonlinear relationship between variables. In our study, the BDS statistics is based on the residuals of each equation of the estimated VAR model with optimal lags.

Table 3 reports the results of the parameter stability tests. As indicated in Table 3, from both the Chow and the Bai and Perron tests, we can reject the null hypothesis of parameter stability for the dBp equation at the 5% level. We can also reject the null hypothesis of stability for the dIA equation according to the results of the Chow tests. These suggest that the coefficients are unstable. The BDS tests reject the i.i.d. assumption at the 1% significance level; this indicates that the relationship between dBp and dIA is nonlinear. Overall, our tests show strong evidence of parameter instability, thereby motivating us to use a dynamic approach.

5.3. Full-Sample Quantile Causality Test. To show a preliminary understanding of the quantile causality between investor attention and Bitcoin returns, we first conduct the full-sample test. From Figure 3, we observe that the causality between dIA and dBp varies across quantiles. In Panel A, the
Quantile causality from dIA to Bitcoin returns shows a hump-shaped pattern; this indicates that in the low and high return phases investor attention Granger causes Bitcoin returns in mean, whereas in the moderate return phase the causality in mean is not significant. This is in line with the findings of Li et al. [46], who report the multiscale evidence based on wavelet decomposition. From Panel C, we observe that the causality in mean from Bitcoin returns to attention is significant at quantiles smaller than 0.6 and exhibits a unimodal shape, which shows strong evidence of causality in the low and moderate attention phases. It also demonstrates that in the high attention phase, Bitcoin returns do not Granger cause investor attention in mean. The findings of causality in mean between Bitcoin returns and investor attention are consistent with those of Li et al. [46] and Subramaniam and Chakraborty [47].

We add to the literature that our results provide the evidence of causality in volatility between Bitcoin returns. From Panel B, we find that the causality in volatility from investor attention to Bitcoin holds only in the moderate quantiles, which is precisely opposite from that of the causality in mean. Combining the results of causality in mean and in volatility, we conclude that during the sample period investor attention Granger causes Bitcoin returns in all quantiles. In Panel D, the causality in volatility from Bitcoin returns to investor attention is significant at quantiles...
5.4. Rolling-Window Quantile Causality Test. Given the possible misleading results caused by parameter instability, we investigate the time- and quantile-varying causality by estimating the rolling window with a fixed size of 100 days. When using rolling-window estimation, we must trade off its accuracy and representativeness influences, which is a key problem [59]. However, there is no widely accepted standard, so we choose the window according to the data. Specifically, we obtain the average length of time for a diminishing trend or an increasing trend using an H-P filter. We then choose the average length of 100 as the size. For the purpose of robustness, we reestimate the model using sizes of 120, 150, 200, and 80 days. The results are similar across various sizes. We plot the empirical results by assigning the results of one window with a fixed size to those of the middle day. For instance, the window from July 6, 2011, to October 13, 2011, is dated August 25, 2011. The results plotted in Figures 4–7 provide strong evidence of quantile- and time-varying causality between the two variables, which supports the idea that linear causality methods are not applicable in our study.

Figure 4 plots the test results of the causality in mean from dIA to dBP. As indicated in Figure 4, the null hypothesis that dIA causes dBP in mean is time varying. Different from the existing full-sample results (e.g., Li et al. [45]; Li et al. [46]; Subramaniam and Chakraborty [47]), our results provide strong evidence that the causality holds not at all times. For example, the causality is significant during the subperiods January 2012 to May 2012, April 2016 to November 2016 and April 2018 to February 2019, whereas the causality disappears during the subperiods September 2011 to December 2011, January 2014 to May 2015, and September 2017 to March 2018.

It is interesting that much of the causality holds when investors pay more attention to Bitcoin. From Figures 1 and 2, we observe that Bitcoin price and Google search volume are significantly positively correlated. However, the positive correlation does not always appear. The correlation becomes negative when Bitcoin price falls sharply. From the figure, we can conclude that if investor attention becomes higher, then the causality from attention to Bitcoin returns is more significant. Thus, the relationship between attention and the causality from dIA to dBP in mean is closer than that between Bitcoin price and the causality. However, there is an exception, that is, in 2017, when attention rises sharply, the causality does not appear. The possible reason is that in 2017, Bitcoin price rises sharply and attracts more attention, but the risk of bubble bursting leads some investors to leaving the market.

In addition, the time variations in the causal relationship are also related to the volatility of cryptocurrencies. For example, we can reject the null hypothesis only in high volatility periods, and during low volatility periods, we find little evidence of the causality from dIA to Bitcoin returns. One possible explanation is that news and policies about Bitcoin may lead to more investor attention and induce more causality from investor attention to Bitcoin returns. By enlarging Figure 4, we find evidence of a hump-shaped pattern across quantiles at each time point, regardless of high or low volatility periods. This interesting finding is consistent with the full-sample result reported in Panel A of Figure 3, which confirms the consistency of our rolling-window results. Our conclusion is inconsistent with Shen et al.’s [35] conclusion, but is consistent with Li et al. [45], Li

### Table 2: Unit-root test results.

| Variable | ADF test | KPSS test |
|----------|----------|-----------|
| lnIA     | Constant | None      | Constant |
|          |          |           |          |
| lnBP     |          |           |          |
| dIA      | -3.4360* |          |          |
| dBP      | -0.6085  |          |          |

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The null hypothesis of the KPSS test is that the variable is stationary.

### Table 3: Results of the parameter stability tests.

| Dimension | BDS test | Chow test | Bai-perron test |
|-----------|----------|-----------|-----------------|
|           |          | Breakpoint dates |          | F statistic | Breaks | F statistic |
| dIA → dBP |           | 4/9/2012 | 4.7084*** | 2 | 10.0733** |
| dIA → dIA |           | 10/17/2011 | 2.1035 | 2 | 6.4516 |

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "−" indicates "does not Granger cause". The optimal lag of the VAR is set based on the Schwarz criterion. "−/−/−/−" means "month/date/year".

### Complexity

smaller than 0.15 and exhibits a diminishing trend. In sum, our results support the existing literature that the causality in mean from Bitcoin returns to investor attention is more significant than that from investor attention to Bitcoin returns, and our results of causality in volatility also show the similar conclusion.
et al. [46], and Subramaniam and Chakraborty [47]. Our results show that the causality from dIA to dBP is significant only in certain cases. Therefore, when investing in Bitcoin, investors should view investor attention as one of the important factors when the market is volatile and pay more attention to other factors when the market is stable.

Figure 5 displays the results of the causality in volatility from dIA to dBP. As indicated in Figure 5, the null hypothesis that dIA causes dBP in volatility is time varying. Different from the significance of the causality in mean, the causality in volatility is not significant in most of the sample period, which is consistent with the result of the full sample. The null hypothesis that dIA does not cause Bitcoin in volatility can be rejected only during high volatility periods. From the results of the subsamples, the causal relationship presents three forms: unimodal, bimodal, and decreasing, which is inconsistent with the unimodal causality from the full-sample result reported in Panel B of Figure 3. However, the unimodal causality dominates the full-sample period, which may be the reason that the full-sample result shows unimodal causality. In addition, we find that decreasing causality holds for the period 2015 to 2017, and bimodal causality appears from 2018 to 2021. By comparing Shen et al.’s [35] results, we find that our results are not the same as theirs. In their research, investor attention Granger causes Bitcoin volume, realized volatility and returns, through linear and nonlinear causality methods. The possible reason is that they do not consider the quantile relationship, and the data they used are Twitter data. Overall, our results tend to suggest that changes in investor attention cause Bitcoin price volatility only in the median quantiles during high volatility periods.

It is understood that investor attention moves asset prices. However, in theory, large changes in asset prices may attract more attention. Figure 6 displays the results of the causality in mean from dBP to dIA. Obviously, the causality in Figure 6 is easier to distinguish than Figures 4 and 5. From the results of the subsamples, the causal relationship
presents two forms: unimodal and decreasing. However, the full-sample result show unimodal causality. Generally speaking, the unimodal causality dominates the sample period, and the decreasing causality appears only in a few subperiods. The unimodal causality means that higher or lower investor attention will disrupt the impact of changes in Bitcoin returns on investor attention. Only in the case of moderate investor attention, changes in Bitcoin returns affect investor attention. The possible explanation is that, higher or lower investor attention is mainly determined by other factors, such as changes in regulatory policies, financial market crises, and monetary policy, and changes in Bitcoin price have less impact on investors’ attention, leading to insignificant causal relationship.

For the time domain, we reject the null hypothesis that dBp does not cause dIA only during high volatility periods. In particular, the quantile causality in 2013 is more significant than in other periods. One possible explanation is that the European Cyprus incident in 2013 made European safe-haven funds to start paying attention to Bitcoin, and the subsequent sharp price increase leads to the global existence of Bitcoin. Significant causality from dBp to dIA implies that large changes in Bitcoin prices attract more attention. Our conclusion is inconsistent with Shen et al.’s [35] conclusion, who find no evidence that Bitcoin returns cause investor attention, and with Li et al. [45], Li et al. [46], and Subramaniam and Chakraborty [47], who find strong evidence that Bitcoin returns do cause investor attention, which is because we use a time-varying approach.

Figure 7 displays the results of the causality in volatility from dBp to dIA. Obviously, the causality reported in Figure 7 is easier to distinguish than Figures 5 and 6. For the
time domain, we find that the null hypothesis that dBP volatility does not cause investor attention volatility can be rejected only during high volatility periods. The significant subperiods include February 2013 to October 2013, December 2016 to October 2017, and January 2019 to October 2020. We also find that the statistics of causality in different sub-periods changes dramatically and shows a decreasing trend. In addition, Figure 7 shows that the causality presents a diminishing trend for the quantile domain. This suggests that when dBP and dIA are lower, the causality in volatility is more significant. These findings are consistent with the full-sample results reported in Panel D of Figure 3. The possible reason for the diminishing causality for the quantile domain is that when investors pay less attention to Bitcoin, price fluctuations are relatively large, so price fluctuations are more likely to attract investors’ attention. This implies that we should pay more attention to the impacts of the sharp drop in Bitcoin prices on market expectations, investor attention, and other factors when investing. Our empirical results suggest that investor attention is an important factor affecting the Bitcoin price, but this influence is not always present and has time-varying heterogeneity. For policymakers, it is necessary to intervene Bitcoin market and manage risks according to specific circumstances. Moreover, it is necessary to pay attention to the spiral effect of Bitcoin returns and investor attention.

6. Conclusions

The sharp volatility prevailing in cryptocurrencies prices necessitates the investigation of behavioral aspect in the pricing of cryptocurrencies. Limited cognitive investors in
financial markets motivate us to explore the attention-driven changes in cryptocurrencies prices. Thus, we aim to analyze the impact of investor attention on the price movement of the most important cryptocurrency, that is, Bitcoin. To captures the heterogeneity and time variations in the causality between investor attention and Bitcoin returns simultaneously, this study develops a rolling-window quantile-causality test and uses Google Trends data to investigate the time-varying quantile causality. The results from a set of structural change tests show that the parameters for the causality tests are significantly unstable during the sample period. The results from the rolling-window causality test also show strong evidence of quantile- and time-varying causality between investor attention and Bitcoin returns. Specifically, our results show that the causality appears only in high volatility periods within the time domain, and causality presents various patterns across quantiles within the quantile domain.

Our findings have three implications. First, the results show similar patterns across quantiles and subsamples, which are beneficial for investors. Investors should pay more attention to the impacts of sharp drops in Bitcoin prices on market expectations, investor attention, and other factors when investing. Second, the finding that investor attention- Bitcoin price causality is significant only during volatility periods can be used for supervisors and investors. Thus, when investing in Bitcoin, investors should view investor attention as one of the important factors when the market is volatile and pay more attention to other factors when the market is stable. Third, although our results show evidence of causality between investor attention and Bitcoin returns, whether the relationship holds for other similar assets is still unclear; after all, Bitcoin is only one of various cryptocurrency assets. In addition, this study also has the following limitations. First, the rolling-window method is not the best way to investigate the time-varying causality between investor attention and Bitcoin returns. The causality of subsamples cannot precisely stand for the causality of a certain day. To improve the accuracy of time-varying causality tests, the following studies may focus on the time-varying Bayesian estimation methods. The second is that this study only focuses on Bitcoin, which has greater influence and representativeness, but recent studies have shown that Bitcoin’s dominance is being weakened. Thus, future researches can be extended to other cryptocurrencies. In addition, for the selection of indicators, we can further compare the causal relationship between attention and cryptocurrencies returns using different proxies for investor attention.

Data Availability

The original data were obtained from Google Trends (http://trends.google.com) and Bitcoinity (https://data.bitcoinity.org).

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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