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Can Economic Policy Uncertainty, Volume, Transaction Activity and Twitter Predict Bitcoin? Evidence from Time-Varying Granger Causality Tests

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Abstract

We examine the predictive power of economic policy uncertainty, volume, transaction activity, and Twitter on Bitcoin between 27 December 2013 and 11 February 2019 using the recently proposed time-varying Granger causality tests of Shi *et al.* (2018). First, of particular interest, we show that volume can only predict Bitcoin returns during two episodes (August 2016-January 2017 and May 2017-June 2017) based on a Wald test with a recursive evolving procedure under a homoskedasticity error assumption. However, volume cannot predict volatility under any specifications. Secondly, both US economic policy uncertainty and equity market uncertainty indices, which are used as proxies for policy uncertainty, have no effect on predicting Bitcoin returns. Thirdly, transaction activity also cannot predict Bitcoin returns. Lastly, the number of tweets about Bitcoin can Granger cause the volume of Bitcoin (for example, March 2015-August 2015 and January 2016-February 2019) but not returns or volatility.

JEL Classification

C12, C32, G12, G15

Keywords

Bitcoin
economic policy uncertainty
volume
transaction activity
Twitter
time-varying Granger causality

1. Introduction

Cryptocurrencies, especially Bitcoin, have attracted extraordinary attention from academics. For example, Urquhart (2016), Nadarajah & Chu (2017), Jiang et al. (2018) and Hu et al. (2019) examine the efficiency of Bitcoin; Cheung et al. (2015), Fry & Cheah (2016) and Corbet et al. (2018) investigate the existence of bubble-like behaviour while Dyhrberg (2016a), Dyhrberg (2016b) and Baur et al. (2018) analyse diversification benefits.

A range of studies have attempted to explore the predicative ability of several important variables on Bitcoin returns or volatility. The first by Balcilar et al. (2017) concluded that volume can predict Bitcoin returns at some middle quantiles (the normal market) using a nonparametric causality-in-quantiles test, while volume cannot predict volatility. Aalborg et al. (2019) point out that the transaction volume of Bitcoin, change in the number of unique Bitcoin addresses, the VIX index and Google searches for "Bitcoin" cannot predict Bitcoin returns. Bouri et al. (2019) study the Granger causality from trading volume to the returns and volatility for Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, and Stellar based on a copula-quantile approach. They report that trading volume Granger causes extreme negative and positive returns (low and high quantiles) of all cryptocurrencies under consideration. However, volume Granger causes volatility (proxied by squared Bitcoin returns) for only three cryptocurrencies (Litecoin, NEM, and Dash) at the low quantiles. Demir et al. (2018) confirm the predictive power of the economic policy uncertainty (EPU) index on daily Bitcoin returns. Urquhart (2018) examines the relationship between investor attention (Google Trends data) and Bitcoin returns, realized volatility or volume using vector autoregressive (VAR) models and a Granger causality test, and concludes that attention provides no significant predictive power for realized volatility or returns. A recent paper by Shen et al. (2019) finds that the volume of tweets are significant drivers of realized volatility (RV) and trading volume but not for Bitcoin returns based on both linear and nonlinear Granger causality tests.

This paper attempts to explore the predicative ability of policy-related economic uncertainty, volume, transaction activity, and Twitter on Bitcoin from a time-varying perspective. We consider both the US economic policy uncertainty (EPU) index and the US equity market uncertainty (EMU) index developed by Baker et al. (2016) to proxy for the role of policy uncertainty. Similar to a recent paper by Koutmos (2018), the total number of unique Bitcoin transactions and number of unique Bitcoin addresses are used to proxy transaction activity. We also follow Shen et al. (2019) by letting the number of tweets serve as a measure of investor attention. In particular, we use the new time-varying Granger causality test of Shi et al. (2018) to explore the predictive power of several important variables on Bitcoin. This new econometric procedure allows us to detect the origination and collapse dates of episodes of causality as the approach can serve as a new real-time causal identification test procedure.

This paper revisits the following interesting questions considered in Demir et al. (2018), Balcilar et al. (2017) and Shen et al. (2019), respectively:

- 1: Does economic policy uncertainty predict Bitcoin returns? (Is there a causal relationship running from economic policy uncertainty to Bitcoin returns?)
- 2: Does volume predict Bitcoin returns or volatility? (Is there a causal relationship running from volume to Bitcoin returns or volatility?)
- 3: Does Twitter predict Bitcoin returns, volatility or volume? (Is there a causal relationship running from Twitter to Bitcoin returns, volatility or volume?)

We also consider the following question for the first time using the idea from a recent paper by Koutmos (2018).

- 4: Does transaction activity predict Bitcoin returns? (Is there a causal relationship running from transaction activity to Bitcoin returns?)

The remaining parts of the paper are organized as follows. Section 2 describes the data and econometric methods. Section 3 presents the empirical findings and Section 4 concludes.

2. Data and Method

2.1. Description of the Data

We use the daily close prices and volume of Bitcoin between 27 December 2013 and 11 February 2019 from **www.coinmarketcap.com** with 1873 observations. The log Bitcoin return series (r_t) is defined as: $r_t = \log(P_t/P_{t-1})$ and we use the squared values of returns to measure the volatility of the Bitcoin returns.[1] The volume of Bitcoin is the total spot trading volume reported by all exchanges over the previous 24 hours. We use the total number of unique Bitcoin transactions and number of unique Bitcoin addresses from **www.quandl.com**. These two daily data series measure how actively Bitcoin is used in actual transactions. The daily US EPU and EMU indices are obtained from **www.policyuncertainty.com**. The daily number of tweets related to Bitcoin are available at **www.bitinfocharts.com**.[2] The logarithmic change of Bitcoin volume, the US EPU and EMU

[1] We follow the suggestion of Balcilar et al. (2017) to let the squared values of returns to proxy for the volatility of the Bitcoin returns.

[2] For missing values, a zero value is added. We select the Twitter data about Bitcoin from 09 April 2014 to 11 February 2019 giving 1770 observations due to data availability.

indices, the total number of unique Bitcoin transactions, number of unique Bitcoin addresses and the volume of tweets are calculated in the same way as the Bitcoin returns.[3]

2.2. Econometric Framework

The following section is taken from Shi et al. (2018). We can write an unrestricted VAR(p) in multi-variate regression format simply as:

$$\mathbf{y_t} = \mathbf{\Pi x_t} + \varepsilon_\mathbf{t}, \mathbf{t} = \mathbf{1}, \ldots, \mathbf{T} \tag{1}$$

where $\mathbf{y}_t$=$(y_{1t}, y_{2t})^{'}$, $\mathbf{x}_t = (1, \mathbf{y}^{'}_{\mathbf{t-1}}, \mathbf{y}^{'}_{\mathbf{t-2}}, \ldots, \mathbf{y}^{'}_{\mathbf{t-p}})^{'}$, and $\mathbf{\Pi}_{2\times(2p+1)}$=$[\Phi_0, \Phi_1, \ldots, \Phi_p]$. Let $\hat{\mathbf{\Pi}}$ be the ordinary least squares estimator of $\mathbf{\Pi}$, $\hat{\Omega} = T^{-1}\sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_t^{'}$ with $\hat{\varepsilon}_t = y_t - \hat{\pi} x_t$ and $X' = [x_1, \ldots, x_T]$ be the observation matrix of the regressors in Equation 1. In order to test the null hypothesis that y_{2t} does not Granger cause y_{1t}, the Wald test for such restrictions can be denoted as:

$$\mathbf{W} = \left[\mathbf{R}\text{vec}(\hat{\Pi})\right]^{'} \left[\mathbf{R}\left(\hat{\mathbf{\Omega}} \otimes \left(\mathbf{X}^{'}\mathbf{X}\right)^{-1}\right)\mathbf{R}^{'}\right]^{-1} \left[\mathbf{R}\text{vec}(\hat{\Pi})\right], \tag{2}$$

where vec$(\hat{\Pi})$ denotes the (row vectorized) $2(2p + 1) \times 1$ coefficients of $\hat{\Pi}$ and $\mathbf{R}$ is the $p \times 2(2p + 1)$ matrix. Each row picks one of the coefficients to set to zero under the non-causal null hypothesis. There are p coefficients on the lagged values of y_{2t} in Equation 1.

Following the recent bubble detection tests of Phillips et al. (2015), Shi et al. (2018) develop three tests based on the supremum norm (sup) of a series of recursively evolving Wald statistics for detecting changes in causal relationships using a forward recursive, a rolling window and a recursive evolving algorithm. If the Ward statistic sequence exceeds its corresponding critical value, a significant change in causality is detected. The origination (termination) date of a change in causality is identified as the first observation whose test statistic value exceeds (goes below) its corresponding critical values.

The Wald statistic obtained for each subsample regression over $[f_1, f_2]$ with a sample size fraction of f_W ($f_W = f_2 - f_1 \geq f_0$) is denoted by $\mathcal{W}_{f_2}(f_1)$ and the sup Ward statistic is defined as:

$$\mathcal{SW}_f(f_0) = \sup_{(f_1, f_2)\in\Lambda_0, f_2 = f} \{\mathcal{W}_{f_2}(f_1)\}, \tag{3}$$

where $\Lambda_0 = \{(f_1, f_2) : 0 < f_0 + f_1 \leq f_2 \leq 1, \text{and} \quad 0 \leq f_1 \leq 1 - f_0\}$ for some minimal sample size $f_0 \in (0, 1)$ in the regressions. This is known as the recursive evolving procedure.

[3] We don't consider the Google search data on Bitcoin in our paper to investigate the causal relationship between Bitcoin attention and Bitcoin returns as the Google searches data is only available at the weekly frequency during our sample period.

Let f_e and f_f denote the origination and termination points in the causal relationship, which are estimated as the first chronological observation whose test statistic respectively exceeds or falls below the critical value. The dating rules of the rolling and recursive evolving algorithms are given as:

$$\text{Rolling}: \hat{f}_e = \inf_{f \in [f_0, 1]} \{f : \mathcal{W}_f(0) > \text{cv}\} \qquad \text{and} \qquad \hat{f}_f = \inf_{f \in [\hat{f}_e, 1]} \{f : \mathcal{W}_f(0) < \text{cv}\}, \tag{4}$$

$$\text{Recursive Evolving}: \hat{f}_e = \inf_{f \in [f_0, 1]} \{f : \mathcal{SW}_f(0) > \text{scv}\} \qquad \text{and} \qquad \hat{f}_f = \inf_{f \in [\hat{f}_e, 1]} \{f : \mathcal{SW}_f(0) < \text{scv}\}, \tag{5}$$

where *cv* and *scv* are the corresponding critical values of the $\mathcal{W}_f$ and $\mathcal{SW}_f$ statistics. For multiple switches, the origination and termination dates are calculated in a similar fashion. As Shi et al. (2019) suggest, the power of the recursive evolving and rolling window approaches are much higher than that of the forward recursive testing procedure, and the recursive evolving algorithm offers the best finite sample performance. Hence, we investigate the potential causal relationship using these two procedures in this paper.

In estimating the bivariate VAR and implementing tests of Granger causality, the lag order is selected using the Bayesian information criterion (BIC) with the maximum lag length 12. The minimum window size f_0 is set to 0.2, which includes 374 observations.[4] The critical values are obtained from a bootstrapping procedure with 499 replications. The empirical size is 5% and is controlled over a one-year period.[5]

3. Results

This section presents empirical findings on the predictive power of several key variables on Bitcoin.

3.1. EPU-Bitcoin Returns

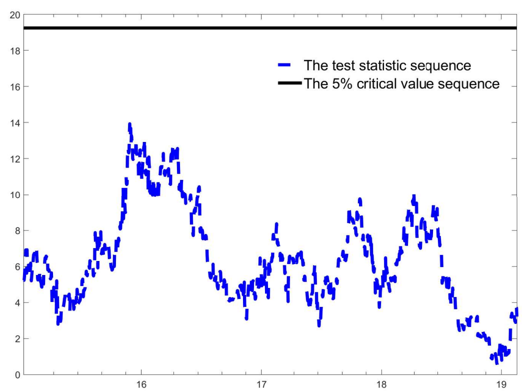
The time-varying Wald test statistics for causal effects from the EPU index to Bitcoin returns along with their bootstrapped critical values are shown in Figure 1. The two rows illustrate the sequences of test statistics obtained from the rolling window and recursive evolving procedures respectively, while the columns of the figure refer to the two different assumptions for the residual error term (homoskedasticity and heteroskedasticity) for the VAR. Sequences of the test statistics start from December 2014.

[4]For the Twitter data about Bitcoin, f_0 is also 0.2 including 354 observations.

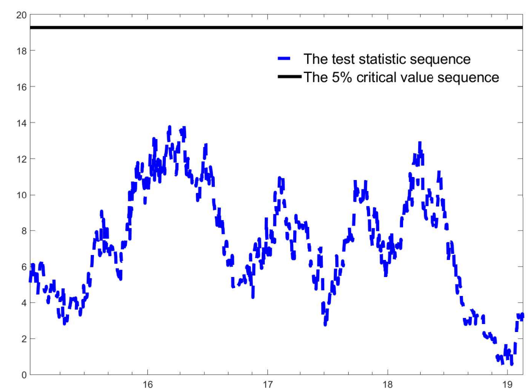
[5]We estimate the VAR model under the null with the whole sample and simulate 374 + 11 = 385 observations for each bootstrapped sample.

All panels in Figure 1 indicate that the test statistics of the predictive power of the EPU index on Bitcoin returns are always below their critical values, suggesting there is no evidence to reject the null hypothesis of no causality. Our results, therefore, suggest that the EPU index cannot predict Bitcoin returns. Alternatively, there is no causal relationship running from the EPU index to Bitcoin returns in all cases.

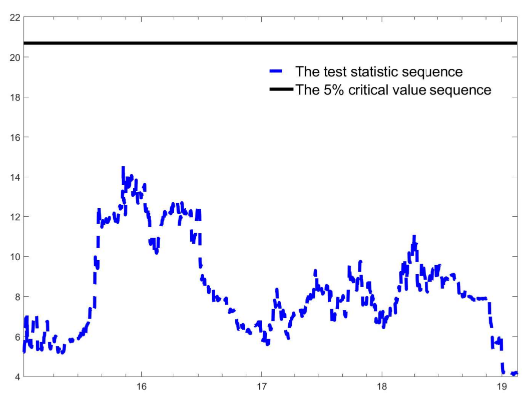
(a) Rolling Window-Homoskedasticity



(b) Rolling Window-Heteroskedasticity



(c) Recursive Evolving-Homoskedasticity



(d) Recursive Evolving-Heteroskedasticity

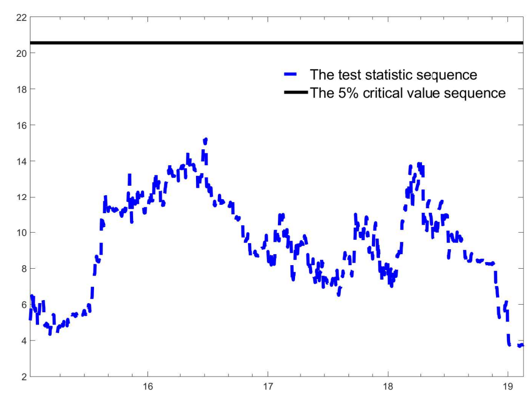
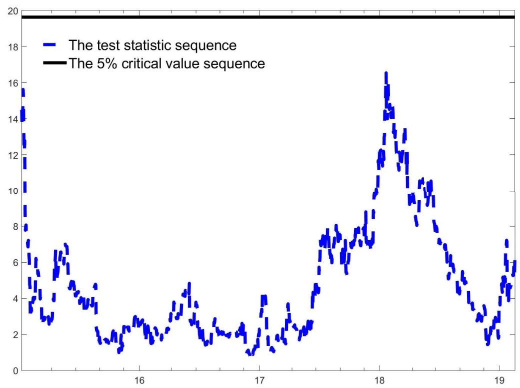


Figure 1: Tests for Granger causality running from the EPU index to Bitcoin returns.

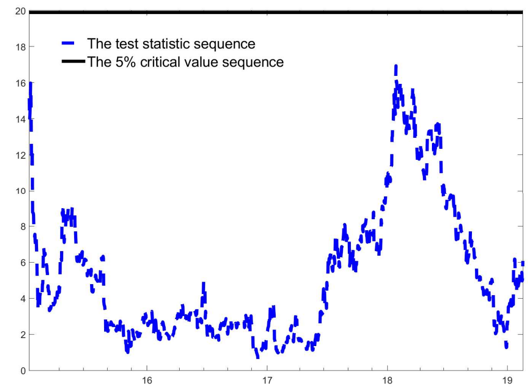
3.2. EMU-Bitcoin Returns

Results from Figure 2 indicate that the EMU index cannot predict Bitcoin returns for all different test specifications or error assumptions as the test statistics are below the critical values. Overall, two indices of EMU and EPU used to proxy policy uncertainty have no significant predictive power to explain Bitcoin returns.

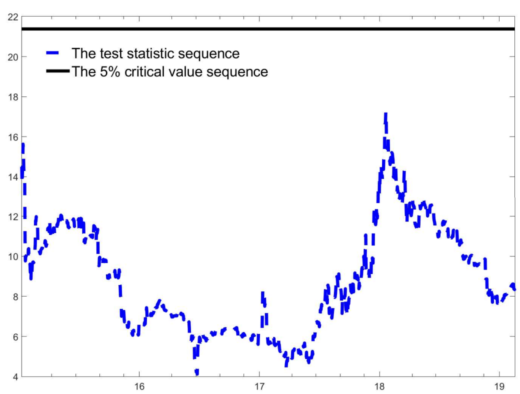
(a) Rolling Window-Homoskedasticity



(b) Rolling Window-Heteroskedasticity



(c) Recursive Evolving-Homoskedasticity



(d) Recursive Evolving-Heteroskedasticity

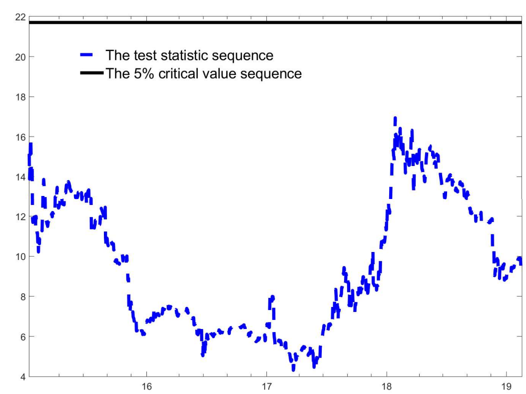


Figure 2: Tests for Granger causality running from the EMU index to Bitcoin returns.

3.3. Volume-Bitcoin Returns

Figure 3 presents time-varying results for causal effects from volume to Bitcoin returns. Based on two different error assumptions, the rolling window approach identifies very short episodes of causality in Figure 3a but finds no episodes of causality in Figure 3b. The recursive evolving procedure provides more striking results under the homoskedasticity assumption, where the null of no Granger causality from the volume to the Bitcoin returns can be rejected (see Figure 3c) as the recursive evolving procedure detects two episodes of causality (August 2016-January 2017 and May 2017-June 2017).[6][7] It seems to suggest that volume can only predict Bitcoin returns during these two episodes, which is one of most important results of this paper. However, no such conclusion can be drawn under the heteroskedasticity assumption in Figure 3d.

3.4. Volume-Volatility

The time-varying causal effects from volume to the volatility of Bitcoin are shown in Figure 4. We can see some very short episodes of causality, however, there is insufficient evidence to reject the null of no Granger causality over the whole sample period.[8] It is fair to conclude that volume cannot predict volatility, which is in line with the conclusion drawn by Balcilar et al. (2017).

3.5. Transaction Activity-Bitcoin Returns

We first use the total number of unique Bitcoin transactions to proxy for transaction activity. As can be seen from Figure 5, there is no causal relationship (or change in the causal relationship) from the total number of unique Bitcoin transactions to Bitcoin returns based on the two different procedures and error assumptions. Therefore, the total number of unique Bitcoin transactions does not predict Bitcoin returns.

As mentioned in Koutmos (2018), the number of unique Bitcoin addresses serves as a robustness check for transaction activity. Figure 6 also shows no evidence of causality from the number of unique Bitcoin addresses to the Bitcoin returns as the test statistics are below the critical values during the sample period. Overall, the number of unique Bitcoin addresses does not predict Bitcoin returns.

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[6] In August 2016, Bitfinex, a major Bitcoin exchange platform in the world and based in Hongkong, was hacked and suffered a security breach as almost 120,000 units of Bitcoin worth about US$72 million were stolen from this exchange platform. As an immediate result, the hack triggered a slump in bitcoin prices of more than 20%. It is estimated that the stolen Bitcoin accounted for 0.75% of all bitcoin in circulation. This security breach was one of major Bitcoin events of 2016. In November 2016, Donald Trump won the US presidential election. His win led to volatility in global financial markets. Global stock indices fell sharply after the news. Investors rushed into the safe haven of gold during the market turbulence, and the gold price increased 2.1% immediately. Some investors consider Bitcoin as a hedge against the economic uncertainty. As a result, there was also a sharp rise about 4% in the value of Bitcoin.

[7] In January 2017, the People's Bank of China tightened its regulation on the country's major Bitcoin exchanges, leading to a drop in trading volume. In April 2017, Japan recognizes Bitcoin as a legal method of payment. From March 2017 to December 2017, the value of Bitcoin increased from US$1000 to nearly US$20000.

[8] This interpretation is similar to those studies on bubble detection using the right-tailed unit root tests of Phillips et al. (2015), where practitioners do not report a short-lived episode as evidence of a bubble.

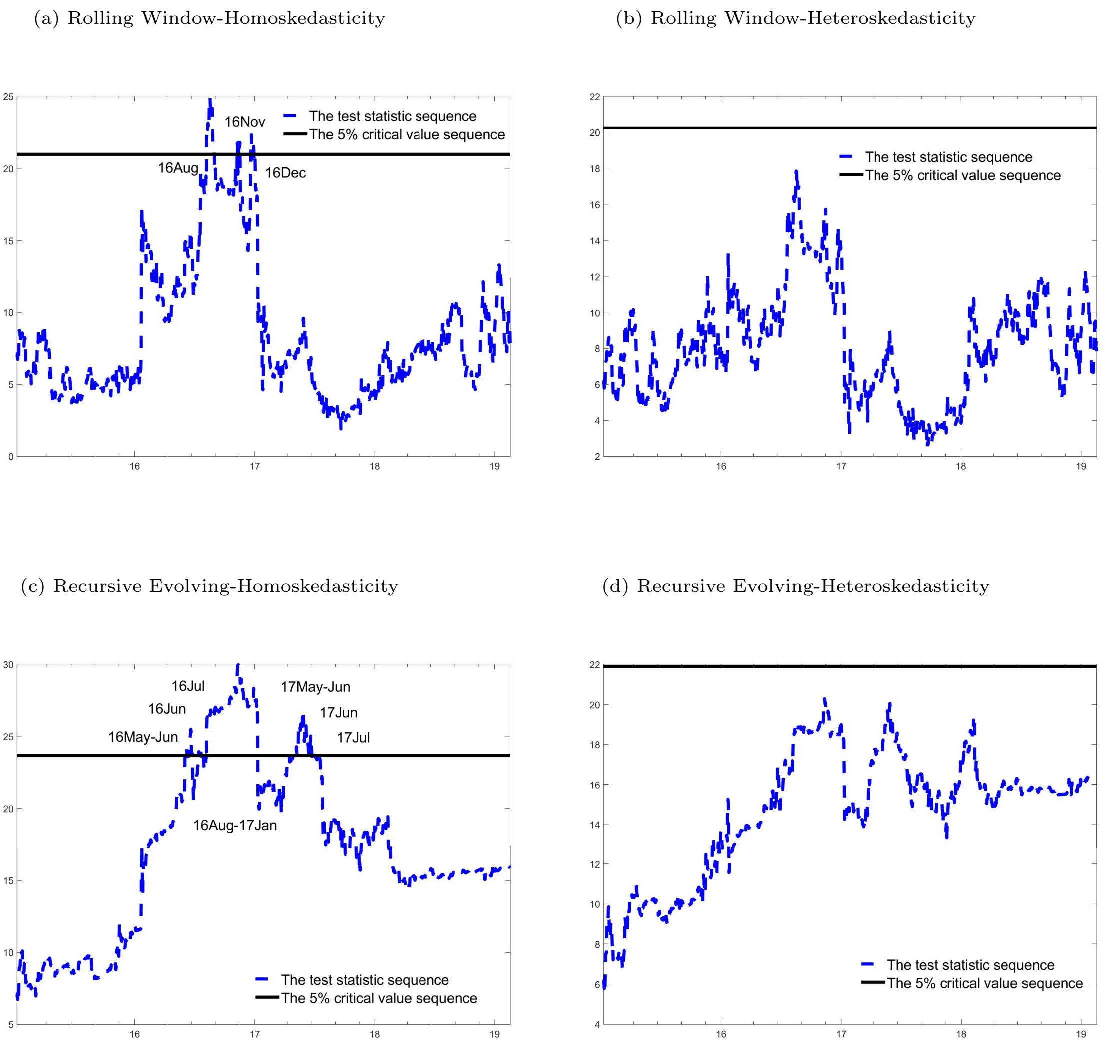


Figure 3: Tests for Granger causality running from volume to Bitcoin returns.

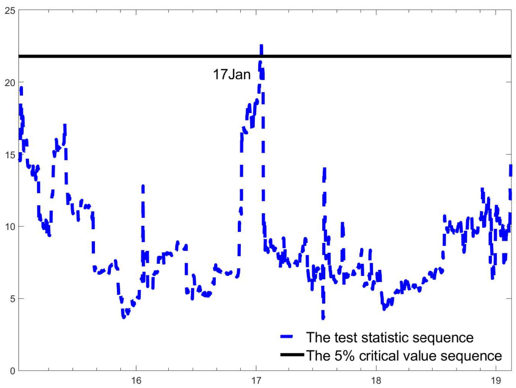
3.6. Twitter-Bitcoin Returns

We next consider whether the number of tweets about Bitcoin can predict Bitcoin returns. As shown in Figure 7, the null of no Granger causality cannot be rejected as the test statistics are below the critical values over the whole sample period. Hence, the number of tweets about Bitcoin have no predictive power on Bitcoin returns from a time-varying test.

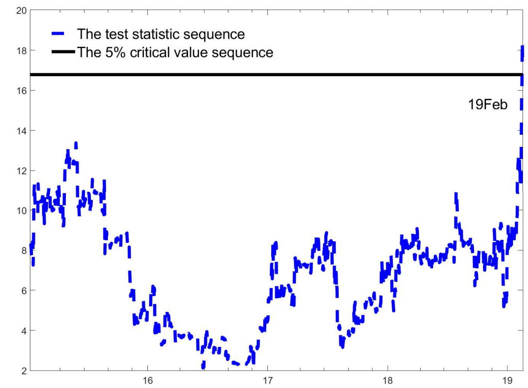
3.7. Twitter-Volatility

We also find no causality episodes under any specifications in Figure 8, indicating that the number of tweets about Bitcoin cannot predict the volatility of Bitcoin.

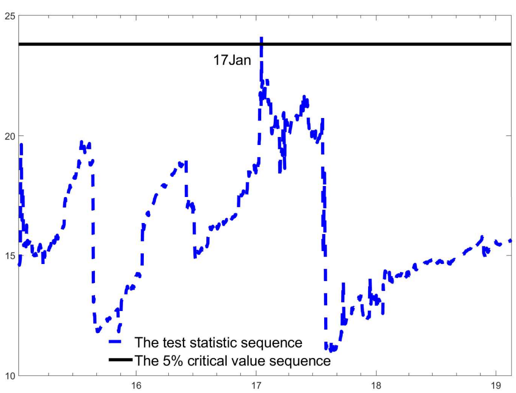
(a) Rolling Window-Homoskedasticity



(b) Rolling Window-Heteroskedasticity



(c) Recursive Evolving-Homoskedasticity



(d) Recursive Evolving-Heteroskedasticity

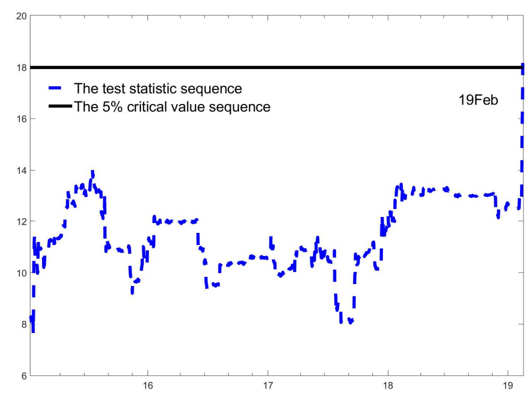
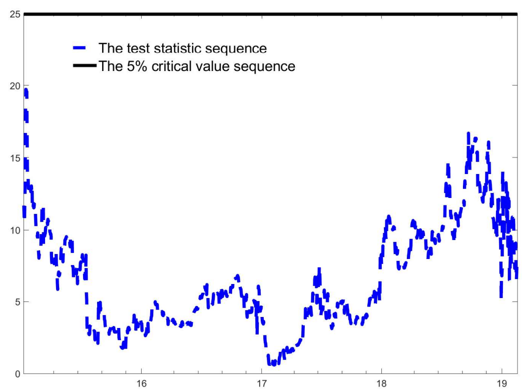


Figure 4: Tests for Granger causality running from volume to volatility.

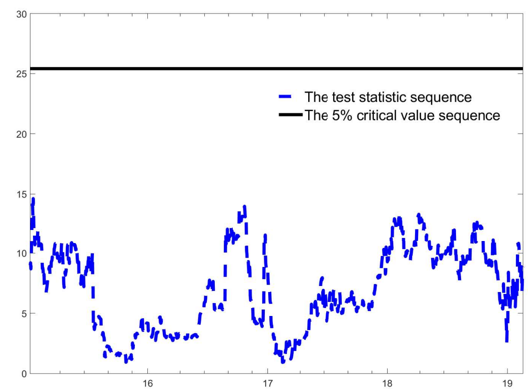
3.8. Twitter-Volume

Some interesting results are obtained from Figure 9, where we explore whether the Twitter data can predict the volume of Bitcoin. The rolling window approach identifies several episodes of causality in each of the error assumptions as shown in Figure 9a and Figure 9b. The recursive evolving approach offers more significant evidence to support Twitter data Granger cause the volume of Bitcoin as two long-lasting episodes of causality are detected (e.g., March 2015-Aug 2015, January 2016-February

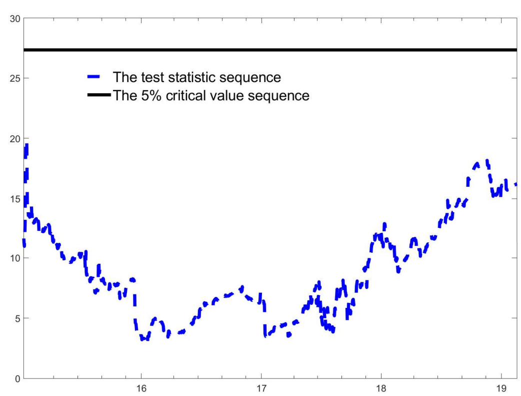
(a) Rolling Window-Homoskedasticity



(b) Rolling Window-Heteroskedasticity



(c) Recursive Evolving-Homoskedasticity



(d) Recursive Evolving-Heteroskedasticity

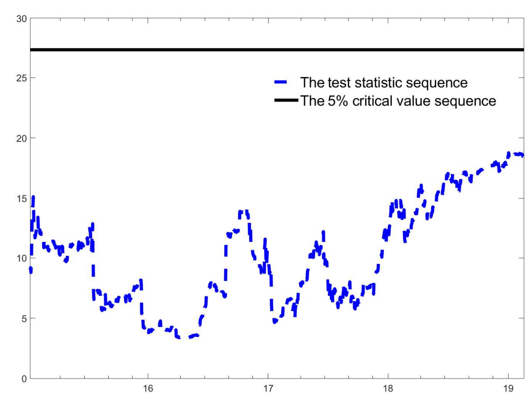
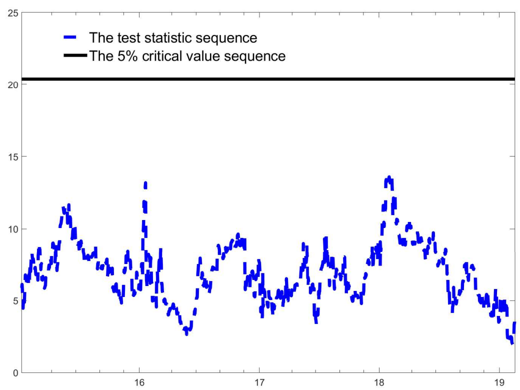
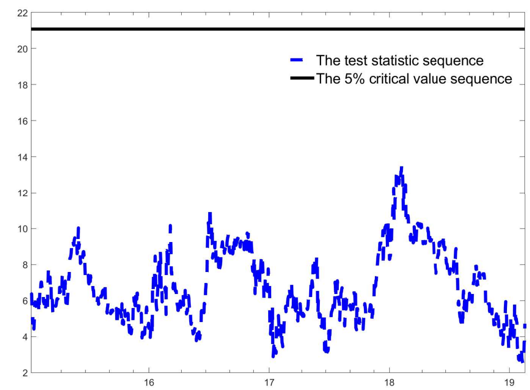


Figure 5: Tests for Granger causality running from the total number of unique Bitcoin transactions to Bitcoin returns.

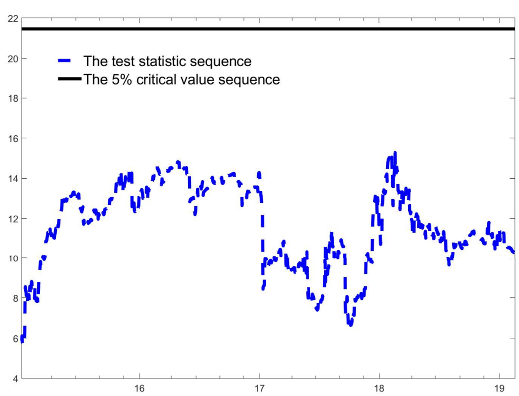
(a) Rolling Window-Homoskedasticity



(b) Rolling Window-Heteroskedasticity



(c) Recursive Evolving-Homoskedasticity



(d) Recursive Evolving-Heteroskedasticity

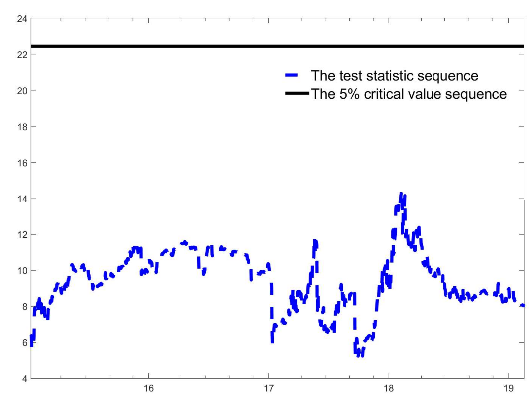
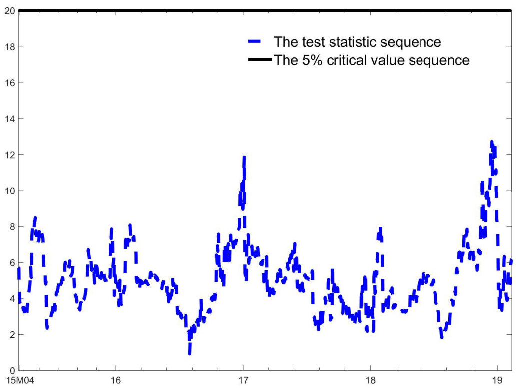
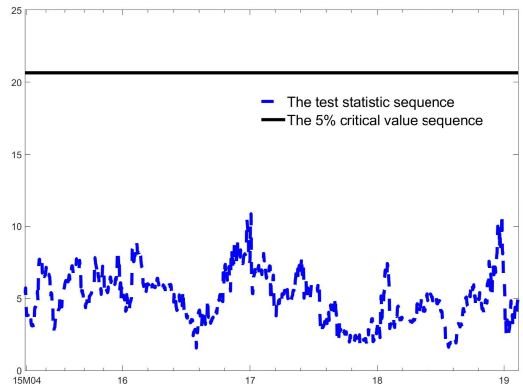


Figure 6: Tests for Granger causality running from the number of unique Bitcoin addresses to Bitcoin returns.

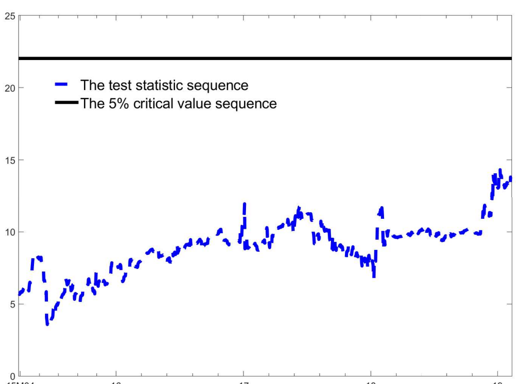
(a) Rolling Window-Homoskedasticity



(b) Rolling Window-Heteroskedasticity



(c) Recursive Evolving-Homoskedasticity



(d) Recursive Evolving-Heteroskedasticity

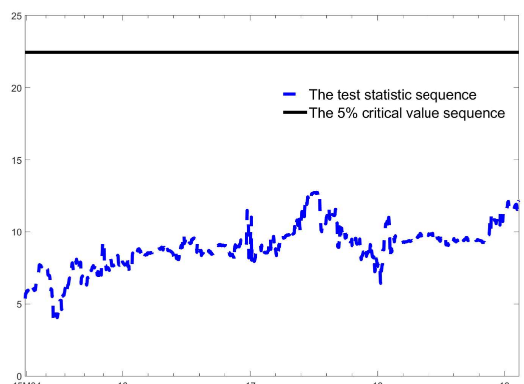
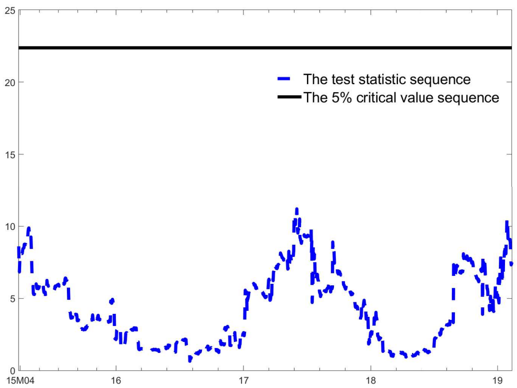


Figure 7: Tests for Granger causality running from Twitter to Bitcoin returns.

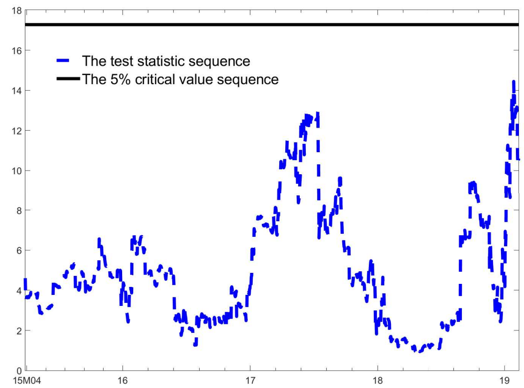
2019) in Figure 9c and Figure 9d, which is of considerable of interest.[9,10]

[9]The Bitcoin price started to fall at the beginning of 2015 until it recovered in October. During 2015, there were several events related to Bitcoin that made the most impact. In January, Bitstamp suffered a major hack and lost about 19000 units of Bitcoin, which was worth US$5.2 million at that time. Late January, Coinbase lunched its own Bitcoin trading platform and raised US$75 million as part of its funding round. In June, the New York Department of Financial Services released the first state specific licensing regulations, which were targeted at digital currency businesses. In August, Mark Karpeles, the former CEO of bitcoin exchange Mt. Gox was arrested in Japan. Mt. Gox was a Bitcoin exchange based in Japan, which handled more than 70% of all Bitcoin transactions in the world. However, this exchange suspended trading in early 2014 and then filed for bankruptcy. It was estimated that 85000 Bitcoins were lost around

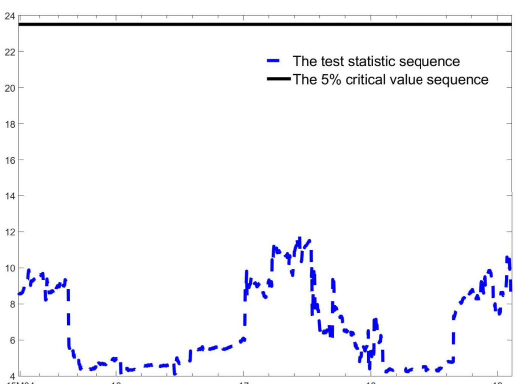
(a) Rolling Window-Homoskedasticity



(b) Rolling Window-Heteroskedasticity



(c) Recursive Evolving-Homoskedasticity



(d) Recursive Evolving-Heteroskedasticity

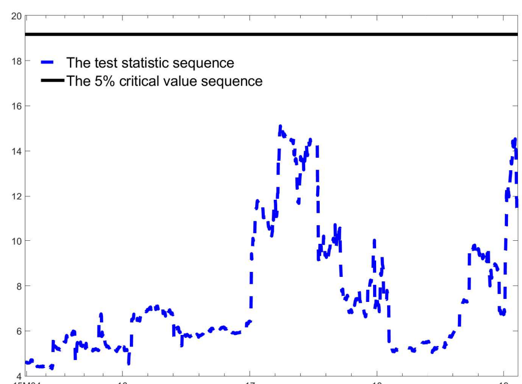


Figure 8: Tests for Granger causality running from Twitter to the volatility of Bitcoin.

US$460 million and about 7% of all Bitcoin in circulation.

[10]Several important events on Bitcoin haven been mentioned in previous footnotes. Here we review the most important events after 2018. In January 2018, Korea warned that it would shut down cryptocurrency exchanges and introduced more regulation for Bitcoin trading. The CoinCheck exchange in Japan was hacked for US$530 million in the same month and the exchange halted all withdrawals. In March, US Securities and Exchange Commission (SEC) announced that all cryptocurrency exchanges must register with the SEC. In September, Goldman Sachs abandoned plans to operate a trading desk. Overall, the price of Bitcoin fell 70% in 2018.

3.9. Robustness check

For all the above analysis, time-varying tests are conducted under the null hypothesis of no Granger causality in a stationary system with lag augmentation d=0. We also carry out a robustness check for a possibly integrated system, see Shi et al. (2019). Hence, the rolling window and recursive evolving procedures are implemented with lag augmentation d=1, where the relevant results are reported in Appendix from Figure A.10 to Figure A.18. Our results still hold.

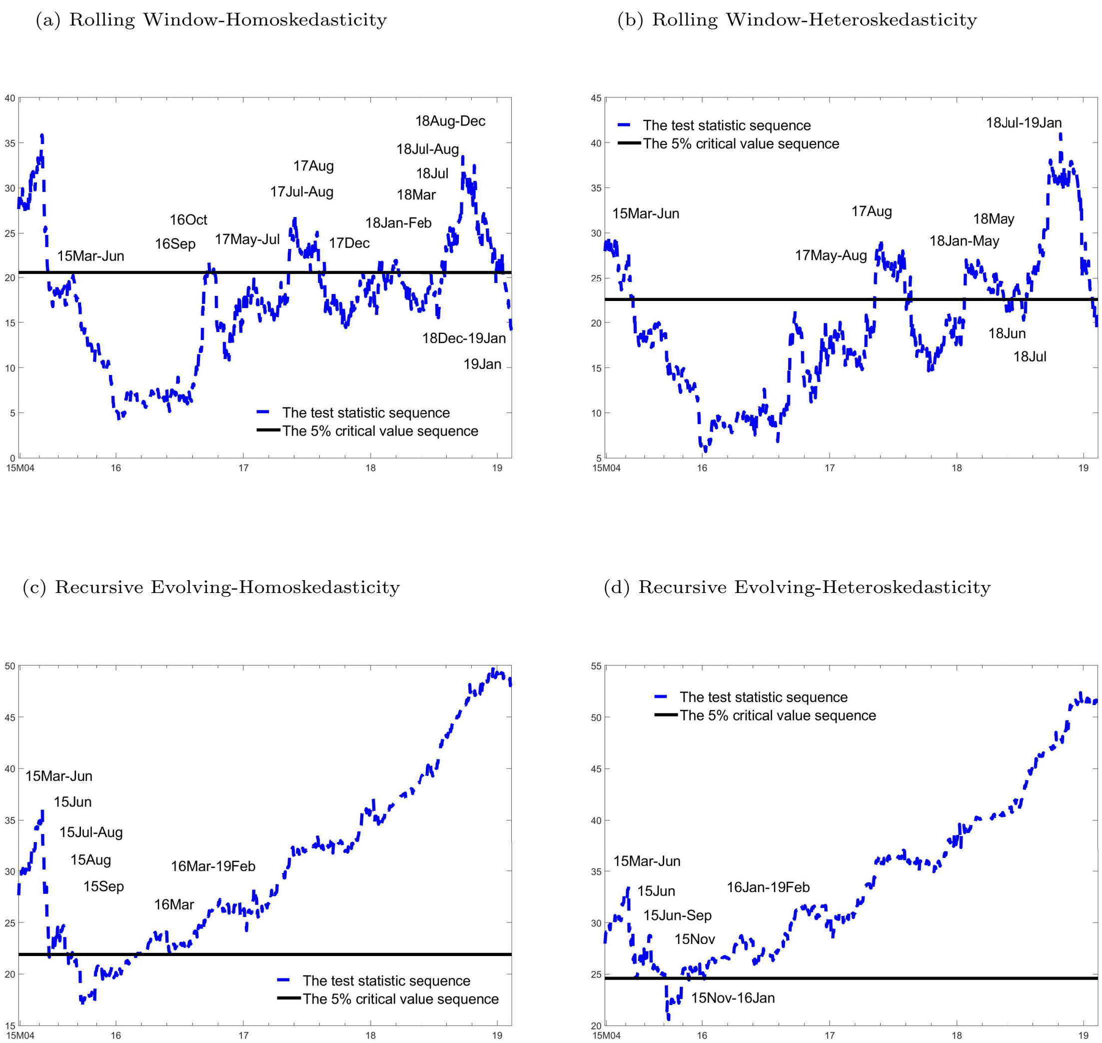


Figure 9: Tests for Granger causality running from Twitter to the volume of Bitcoin.

4. Conclusion

This paper investigates the predictive power of policy-related economic uncertainty, volume, transaction activity and Twitter on Bitcoin between 27 December 2013 and 11 February 2019 based on the time-varying Granger causality tests of Shi et al. (2018). Several interesting and important findings can be summarized as follows. First, volume can only predict Bitcoin returns based on the recursive evolving procedure during two episodes (August 2016-January 2017 and May 2017-June 2017) under the homoskedasticity error assumption while volume cannot predict volatility on any occasion. Second, the EPU and EMU indices have no predictive power for Bitcoin returns. Third, transaction activity represented by the total number of unique Bitcoin transactions and number of unique Bitcoin addresses, also cannot predict Bitcoin returns. Last, Twitter can Grange cause the volume of Bitcoin but not returns or volatility.

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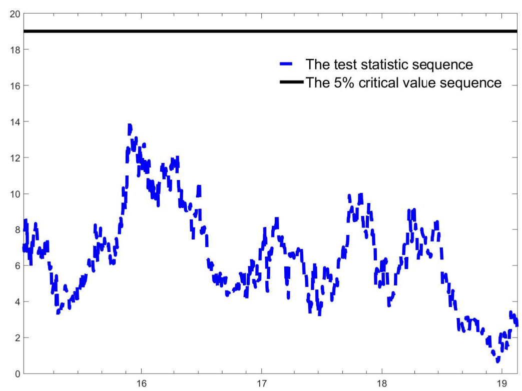
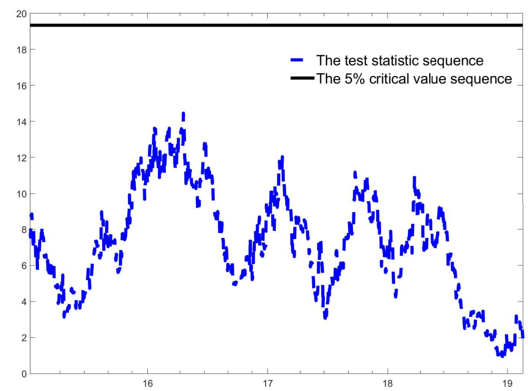
Appendix

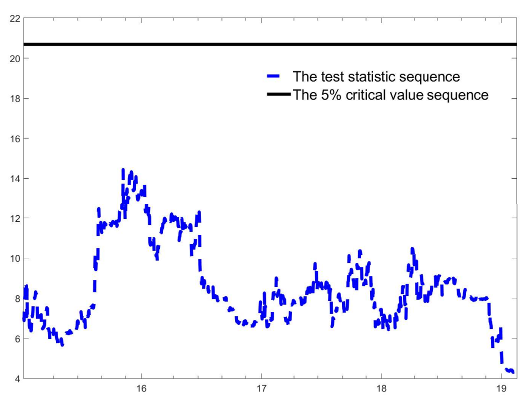
(a) Rolling Window-Homoskedasticity



(b) Rolling Window-Heteroskedasticity



(c) Recursive Evolving-Homoskedasticity



(d) Recursive Evolving-Heteroskedasticity

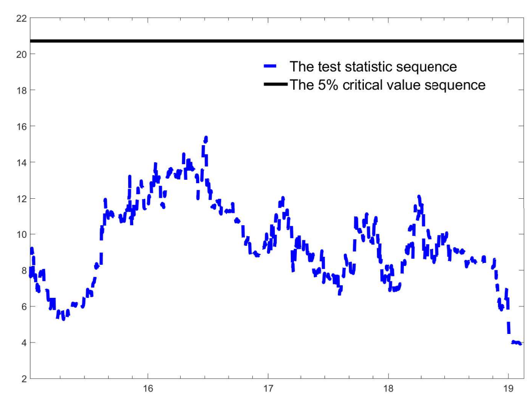
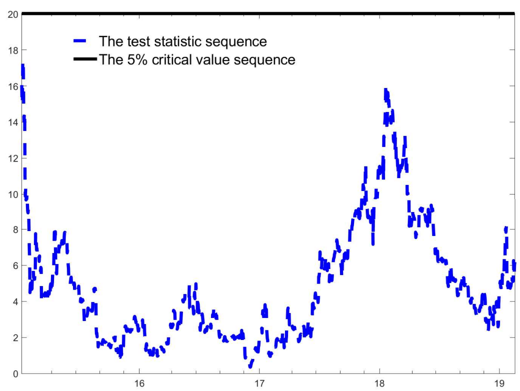


Figure A.10: Tests for Granger causality running from the EPU index to Bitcoin returns with lag augmentation d=1.

(a) Rolling Window-Homoskedasticity



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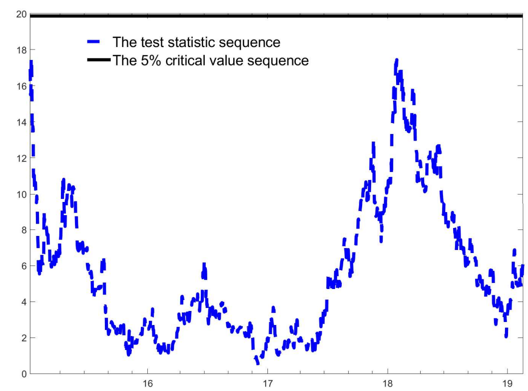
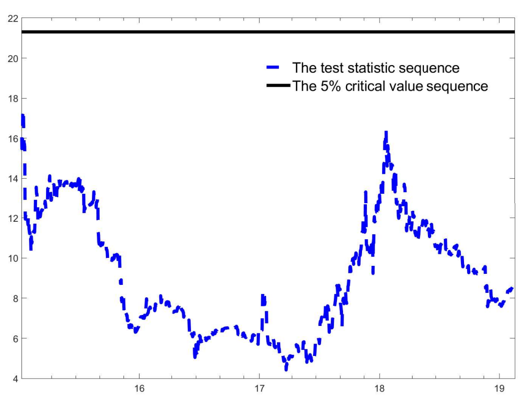


(c) Recursive Evolving-Homoskedasticity



(d) Recursive Evolving-Heteroskedasticity

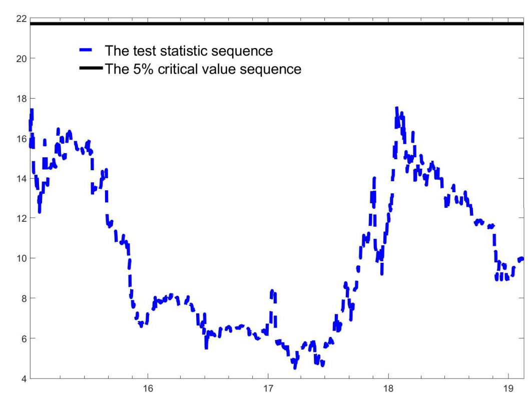
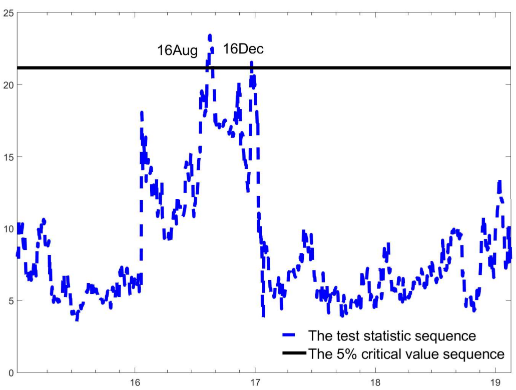
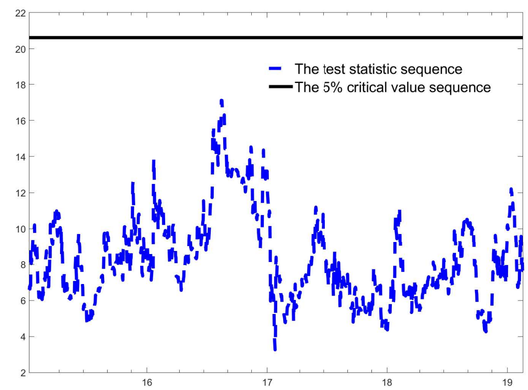


Figure A.11: Tests for Granger causality running from the EMU index to Bitcoin returns with lag augmentation d=1.

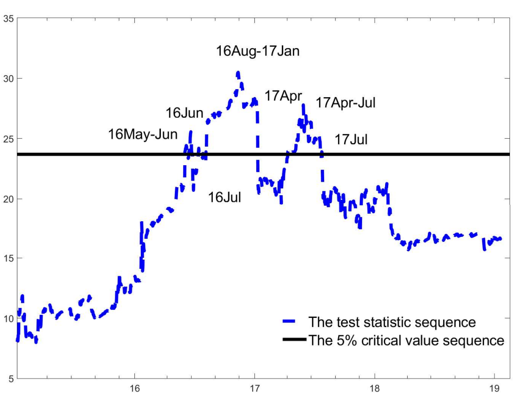
(a) Rolling Window-Homoskedasticity



(b) Rolling Window-Heteroskedasticity



(c) Recursive Evolving-Homoskedasticity



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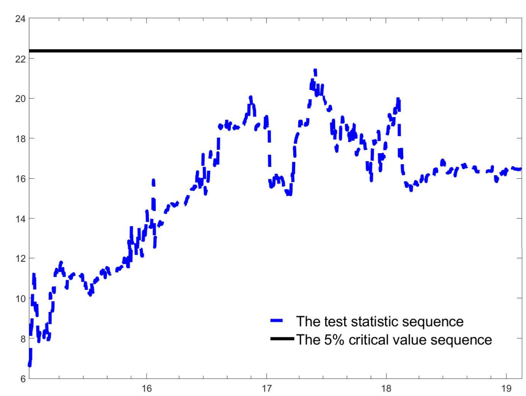


Figure A.12: Tests for Granger causality running from volume to Bitcoin returns with lag augmentation d=1.

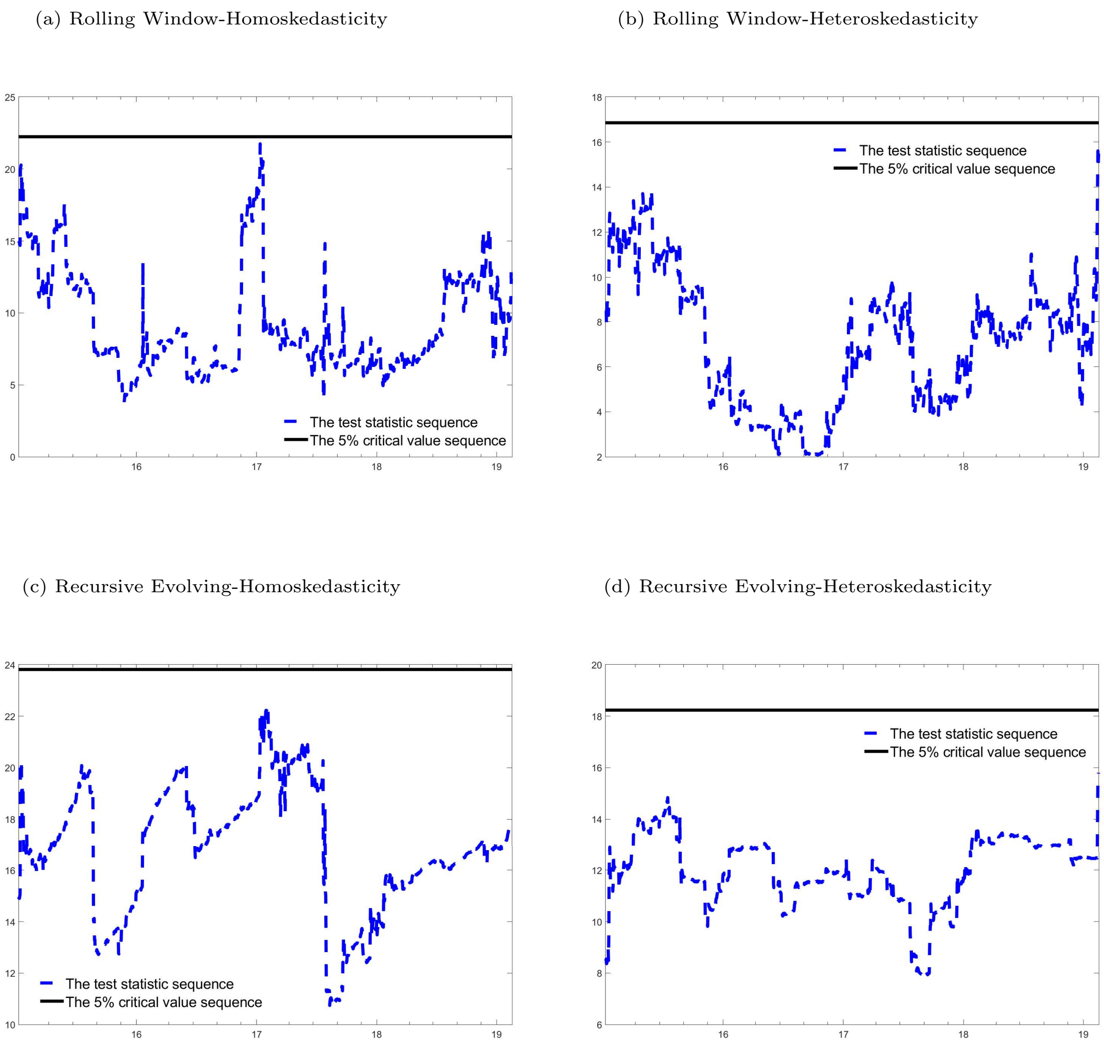
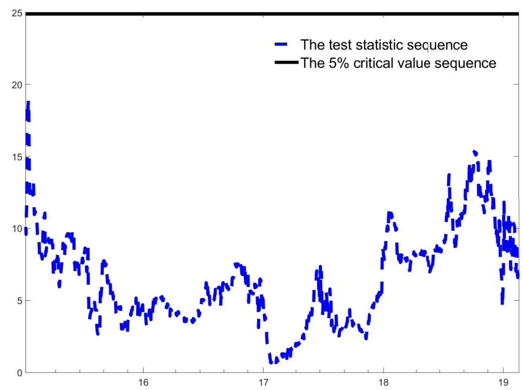


Figure A.13: Tests for Granger causality running from volume to volatility with lag augmentation d=1.

(a) Rolling Window-Homoskedasticity



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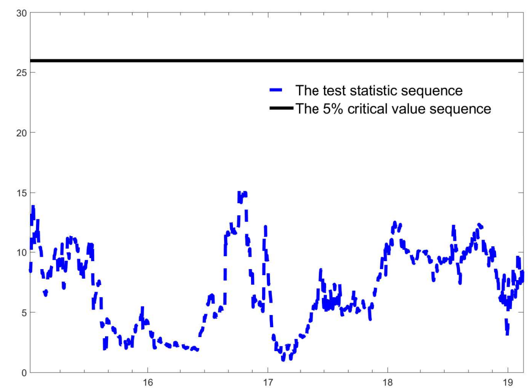
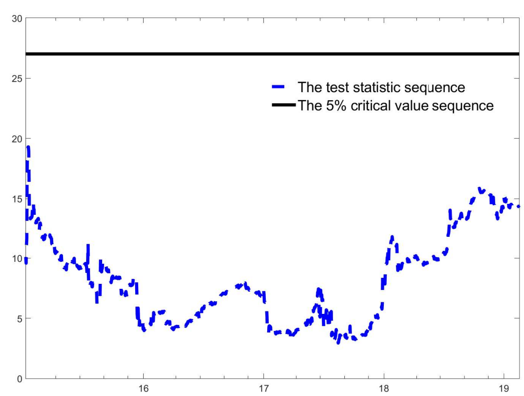


(c) Recursive Evolving-Homoskedasticity



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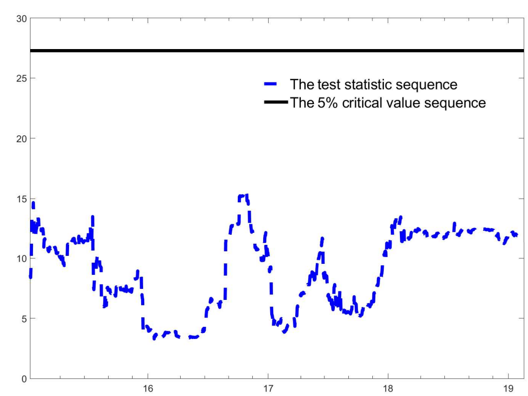
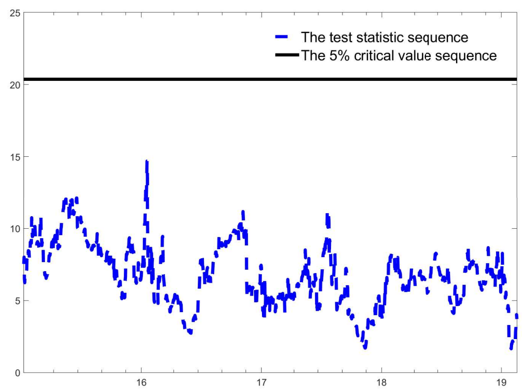


Figure A.14: Tests for Granger causality running from the total number of unique Bitcoin transactions to Bitcoin returns with lag augmentation d=1.

(a) Rolling Window-Homoskedasticity



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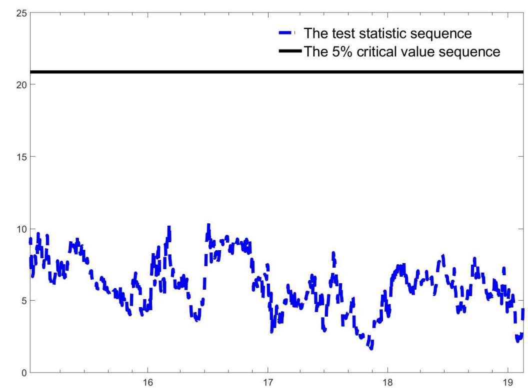
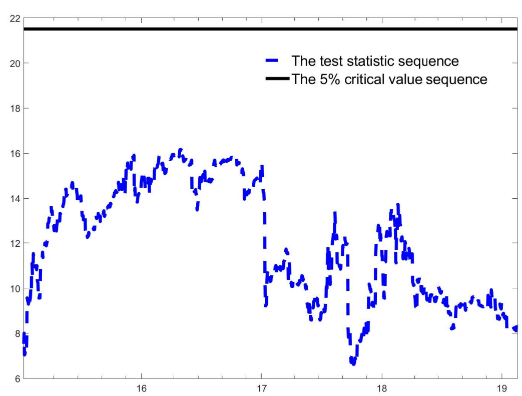


(c) Recursive Evolving-Homoskedasticity



(d) Recursive Evolving-Heteroskedasticity

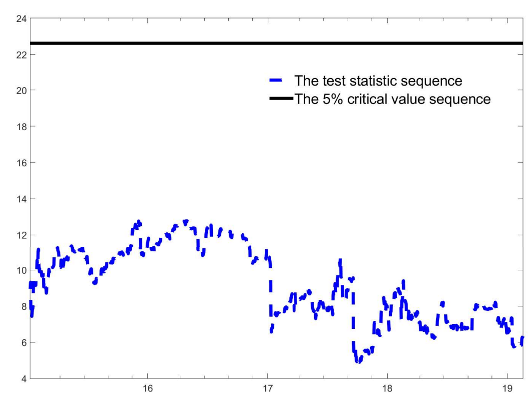


Figure A.15: Tests for Granger causality running from the number of unique Bitcoin addresses to Bitcoin returns with lag augmentation d=1.

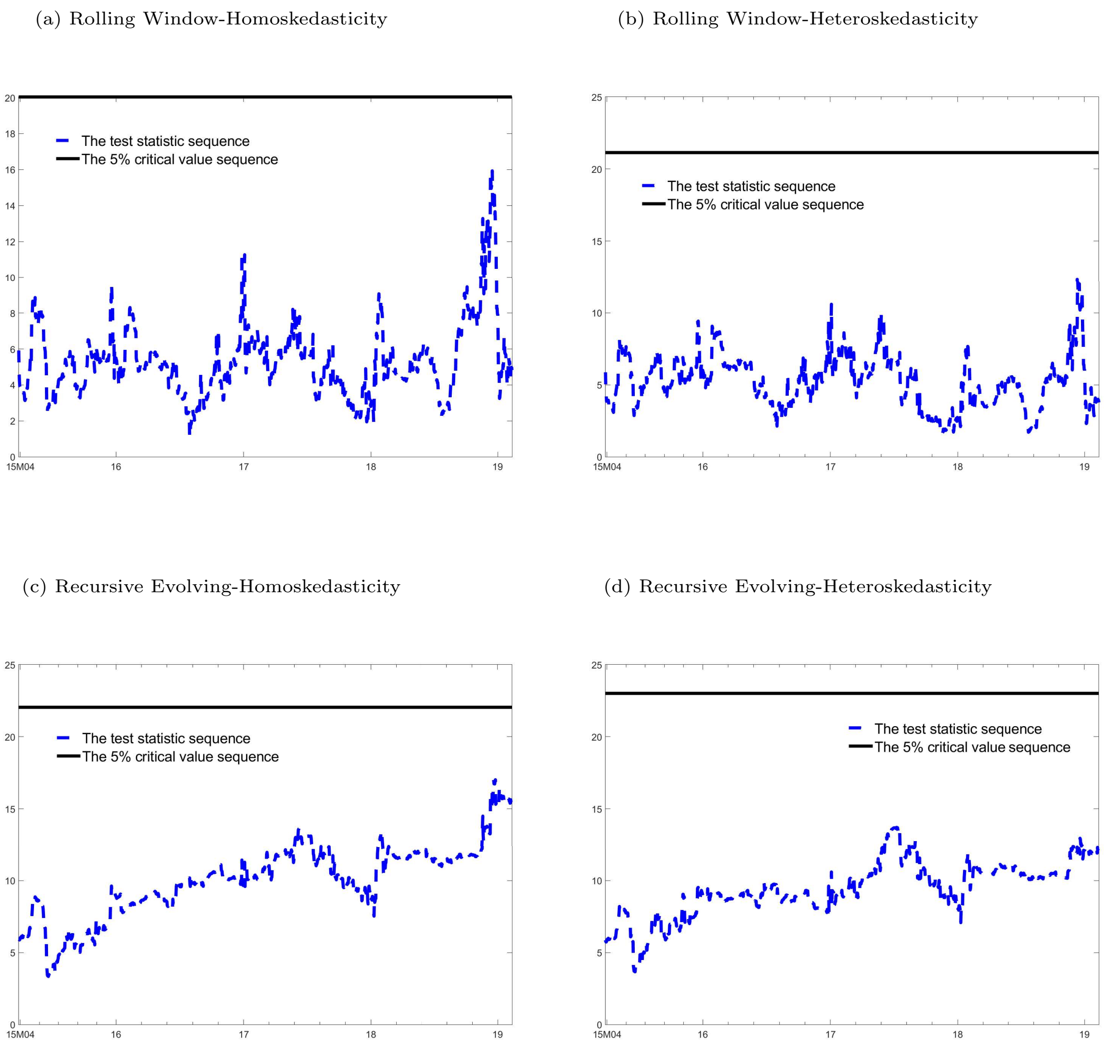
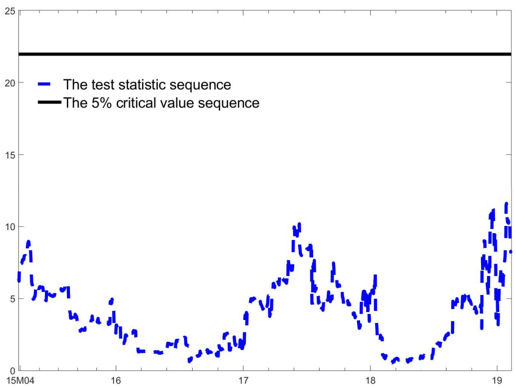


Figure A.16: Tests for Granger causality running from Twitter to Bitcoin returns with lag augmentation d=1.

(a) Rolling Window-Homoskedasticity



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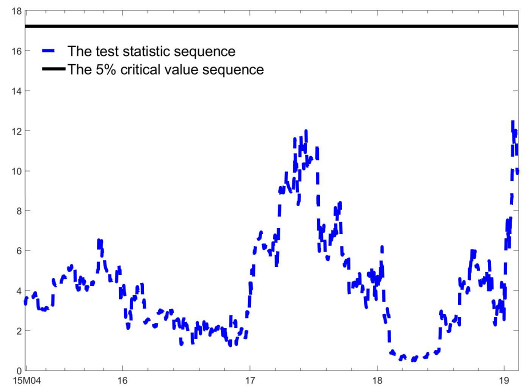

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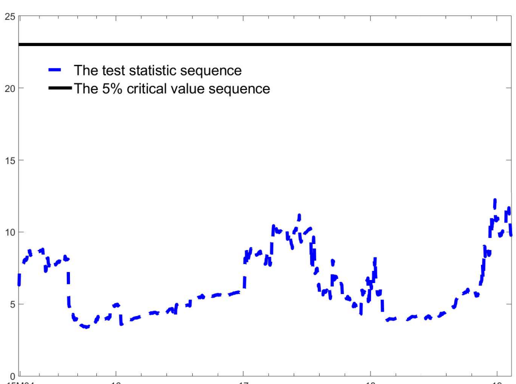


(d) Recursive Evolving-Heteroskedasticity

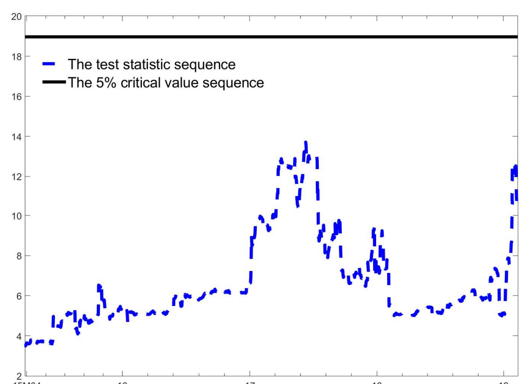
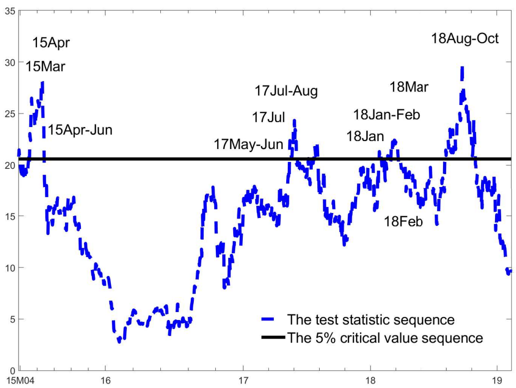


Figure A.17: Tests for Granger causality running from Twitter to the volatility of Bitcoin with lag augmentation d=1.

(a) Rolling Window-Homoskedasticity



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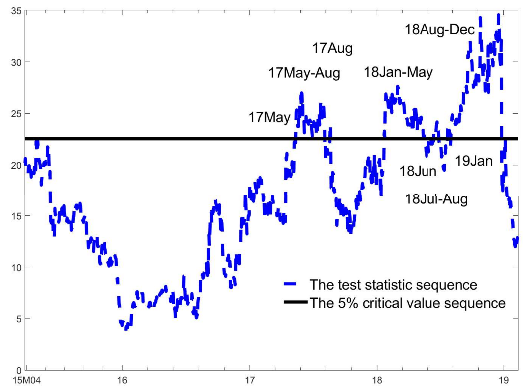
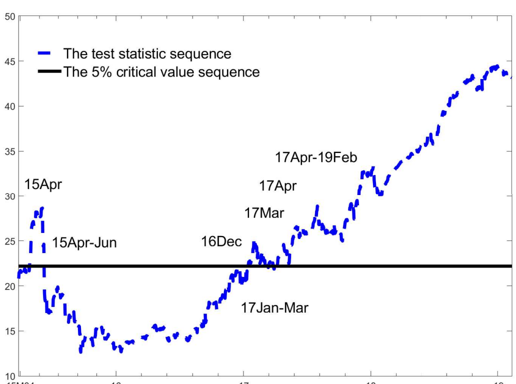


(c) Recursive Evolving-Homoskedasticity



(d) Recursive Evolving-Heteroskedasticity

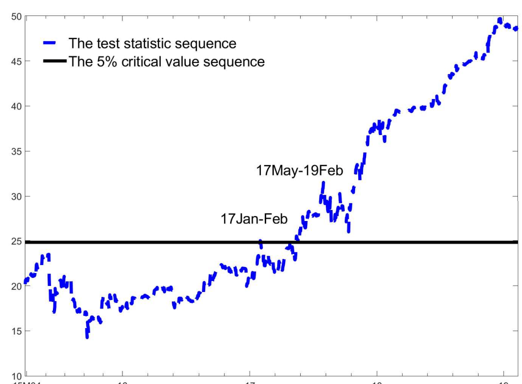


Figure A.18: Tests for Granger causality running from Twitter to the volume of Bitcoin with lag augmentation d=1.