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Stability Analysis of Bitcoin using Recurrence Quantification Analysis

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ABSTRACT Cryptocurrencies are new kinds of electronic currencies based on communication technologies. These currencies have attracted the attention of investors. However, cryptocurrencies are very volatile and unpredictable. For investors, it is very difficult to make investment decisions in cryptocurrency market. Therefore, revealing changes in the dynamics of cryptocurrencies are valuable for investors. Bitcoin is the most popular and representative cryptocurrency in cryptocurrency market. In this study how dynamical properties of Bitcoin changed through time is analyzed with recurrence quantification analysis (RQA). RQA is a pattern recognition-based time series analysis method that reveals dynamics of the time series by calculating some metrics called RQA measures. This method has been successfully applied to nonlinear, nonstationary, short and chaotic time series and does not assume a statistical model. RQA can reveal important properties of time series data such as determinism, laminarity, stability, randomness, regularity and complexity. By using sliding window RQA we show that in 2021 RQA measures for Bitcoin prices collapse and Bitcoin becomes more unpredictable, more random, more unstable, more irregular and less complex. Therefore, dynamics and stability of the Bitcoin prices significantly changed in 2021.

KEYWORDS
Recurrence quantification analysis
RQA
Recurrence plot
Cryptocurrency market
Bitcoin

INTRODUCTION

In the age of information and communication, new digital currencies called cryptocurrencies have emerged (Härdle *et al.* 2020). These cryptocurrencies are operating without a central bank. The decentralized nature of these cryptocurrencies is the result of a technology called blockchain (Yuan and Wang 2018; Tredinnick 2019). These cryptocurrencies have received a lot of attention from investors. Therefore, it is important for investors to reveal the critical changes in the cryptocurrency market.

Cryptocurrency market is a self-organized complex system formed from complex network of traders (Aste 2019). Cryptocurrency prices are output of this complex system. Cryptocurrency prices exhibit high level of nonlinearity, uncertainty and volatility (Chaim and Laurini 2019; Alqaralleh *et al.* 2020). Therefore, prediction of cryptocurrency prices is very difficult (Mezquita *et al.* 2022). However, critical changes in cryptocurrency market can be diagnosed by using recurrence quantification analysis (RQA).

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RQA is a pattern recognition-based time series analysis method which is applied to recurrence plots (RP). Theoretical background of RQA and RP methods is based on how the states of the system is repeated (recurred) during its time evolution. Both RP and RQA reveal the recurrence structure of states of the system in phase space. By analyzing these recurrence structures several judgements can be made on the dynamical properties of the system. A RP can be analyzed visually. In a RP vertical or diagonal lines or isolated points indicate different dynamical properties for the system. In RQA several metrics (measures) are calculated from a RP. These metrics are calculated from the lengths of the vertical and diagonal lines on a RP and reflects dynamical properties of the system. While the RP analysis is dependent on the subjective judgments of the observer, RQA presents a more objective analysis.

Bitcoin is the main cryptocurrency in the cryptocurrency market thus a representative cryptocurrency. In this study our main research question is how stability and dynamic properties of Bitcoin prices have changed during the period 17-08-2017 and 05-10-2021. To carry out this task we utilized sliding window RQA to demonstrate how RQA measures changes through time for Bitcoin. Since RQA measures reflects important characteristics of a time series such as determinism, predictability, randomness, laminarity, stability, regularity and complexity, changes in the RQA measures of Bitcoin reveal the changes of the such characteristics of the Bitcoin prices through time. Our findings reveal that dynamics and stability characteristics of Bitcoin prices significantly changed in 2021. Before 2021 Bitcoin prices quite stable. However, after 2021 Bitcoin prices becomes very unstable and unpredictable. Therefore, we can distinguish two periods in terms of stability for Bitcoin prices. Our main contribution to the literature is that by using RQA we diagnosed dynamical changes in the cryptocurrency market by using the representative cryptocurrency Bitcoin. As far as we know our study is the first study analyzing stability and dynamics of Bitcoin prices using RQA covering the period between 17-08-2017 and 05-10-2021.

Organization of our study is as follows. In the second part we review literature on sliding window RQA. In the third part the methodology is demonstrated. In the fourth part application and results are presented. In the last part study is concluded.

LITERATURE REVIEW

There is a comprehensive bibliography on recurrence plots (RPs), RQA and their applications at the Marwan *et al.* (2013) web site. In this work we utilized sliding window RQA methodology to reveal changes in dynamical properties of Bitcoin through time. In the literature there are few studies applied sliding window RQA to financial time series. Bastos and Caiado (2011) applied RQA to daily data of 23 developed and 23 emerging stock markets between the dates January 1995 and December 2009. By using sliding window RQA, authors demonstrated that during critical economic events such as dot-com bubble, Asian financial crisis and 2008 subprime mortgage crisis, RQA measures laminarity (*LAM*) and determinism (*DET*) decline.

Piskun and Piskun (2011) investigated several stock market crashes by using sliding window RQA and show that RQA measure *LAM* can be used to identify market bubbles. Authors demonstrated that *LAM* measure can be used to distinguish different market periods such as normal functioning, instability, critical period and relaxation.

Sasikumar and Kamaiah (2014) analyzed two Indian stock market indices between 2 January 2002 and 10 October 2013 with sliding window RQA. Authors concluded that Indian equity market has chaotic nature. Also, they demonstrated that RQA measure determinism collapse during the 2008 subprime mortgage crisis and 2010 Euro zone debt crisis. The authors concluded that after 2008 subprime mortgage crisis the market was in turbulent state. Additionally, authors investigated the change in RQA measure *LAM* through time. They showed that laminarity collapsed during the 2008 subprime mortgage crisis. Authors' results for RQA measure trapping time (*Vmean*) confirm that after 2008 subprime mortgage crisis market becomes turbulent.

Moloney and Raghavendra (2012) utilized sliding window RQA to analyze the transition of Dow Jones Industrial Index from bull market to bear market. Authors have particularly interested with events of peaks and subsequent crashes in the dates 1929, 1973, 2000, 2007. Authors discovered that the RQA measures fall soon before or around market peaks. This means that around market peaks, dynamics of the market lose its deterministic structure. Authors detected phase transitions when market transforms from bull state to bear state.

Soloviev *et al.* (2020) analyzed 9 critical periods in the Dow Jones Industrial Average (DJIA) index for the period between 1 January 1990 and 1 June 2019 by using sliding window RQA. Authors demonstrated that during all critical periods RQA measure *DET* shows a downward trend and can detect critical phenomenon. They indicated that *DET*, *LAM*, longest diagonal line (*Lmax*) and trapping time (*Vmean*) are the RQA measures most sensitive to critical events.

Soloviev and Belinskiy (2018) demonstrated possibility of constructing indicators of critical and crisis events in Bitcoin prices using RQA. Authors used daily Bitcoin prices covering the period between 16 July 2010 and 10 February 2018. Authors concluded that RQA measures such as recurrence rate (*REC*), determinism (*DET*) and entropy (*ENTR*) are excellent candidate for a fast, robust, and useful screener and detector of unusual patterns in complex time series.

Soloviev and Belinskiy (2019) used complexity measures to investigate crashes and critical phenomena in the cryptocurrency market. Authors showed that before the crashes and the actual periods of crashes complexity of the market system changes.

In the literature there are few studies applying RQA methodology to Bitcoin. These are Soloviev and Belinskiy (2018, 2019), Kucherova *et al.* (2021) and Bielinskyi and Serdyuk (2021). However, focus of these studies is not to evaluate the dynamical stability of the Bitcoin and these studies do not evaluate the full spectrum of RQA measures but only consider a small subset of RQA measures. Also, data utilized in these studies do not cover recent 2021 data. Focus of Soloviev and Belinskiy (2018, 2019) and Bielinskyi and Serdyuk (2021) is to evaluate the suitability of RQA measures as precursors of crisis and crashes in cryptocurrency market. Focus of Kucherova *et al.* (2021) is to reveal the relationship between the time series of the price of Bitcoin and the frequency of online requests for Bitcoin. The authors used this relationship to illuminate the behavior of agents in the digital economy. After all, as far as we know our study is the first study investigating stability and dynamic properties of Bitcoin prices using broad spectrum of RQA measures and up to date 2021 data.

METHODOLOGY

Recurrence plots (RPs) (Packard *et al.* 1980; Takens 1981; Eckmann *et al.* 1987) are visual analysis tools which portray repetitions of the states of the time series. By visual inspection of RPs dynamics of the underlying time series can be identified. However visual inspection of the RPs has some limitations such as subjective judgement of the observer. To overcome these limitations recurrence quantification analysis (RQA) is developed (Zbilut and Webber 1992; Webber Jr and Zbilut 1994; Marwan *et al.* 2002). In RQA simple pattern recognition algorithms are applied to a RP and measures that describe various properties of the time series are obtained. These analysis tools are successfully applied to nonlinear, nonstationary and chaotic time series in the literature. Main advantages of these tools are that they do not require assumptions such as stationarity, statistical distributions or necessary number of observations. A RP can be expressed by following formula:

$$RP_{ij} = \Theta(T - \|V_i(x) - V_j(x)\|) \tag{1}$$

In the expression above Θ denotes Heaviside step function and T denotes threshold value. If the distance between two state vectors is lower than a threshold value corresponding elements of the recurrence matrix takes the value of one.

In RPs adjacent points have a special meaning. When adjacent points form diagonal lines, this means that states visit same region at different times. Length of these diagonal lines reflects duration of these visits. When adjacent points form vertical or horizontal lines, this means states stay in same region for a duration. RPs belong to deterministic systems display long diagonal lines and few isolated points and RPs belong to stochastic systems display isolated points or very short diagonal lines. In RQA following measures can be calculated:

REC (recurrence rate) quantifies fraction of points in the RP. This metric reflects the likelihood of recurrence of a state. *REC* can be calculated by the following formula:

$$REC = \frac{1}{N^2} \sum_{i,j=1}^{N} RP\left(i,j\right) \tag{2}$$

In the formula above, N denotes the number of points on the constructed phase space.

DET (determinism) quantifies fraction of points in the RP which forms diagonal lines. This metric reflects determinism and randomness in the system. *DET* can be calculated by the following formula:

$$DET = \frac{\sum_{l=l_{min}}^{N} lP\left(l\right)}{\sum_{l=1}^{N} lP\left(l\right)} \tag{3}$$

In the formula above $P\left(l\right)$ represents the frequency distribution of the diagonal lines with length l.

Lmax is the longest diagonal line's length. This metric reflects the stability of the system. High *Lmax* value means high stability and low *Lmax* value means low stability. This metric is also inversely related with largest positive Lyapunov exponent. Lmax can be calculated by the following formula:

$$Lmax = \max\left(\{l_i; i = 1, \ldots, N_l\}\right) \tag{4}$$

In the formula above N_l represents the number of diagonal lines in the RP.

ENTR is the Shannon entropy of the diagonal line length distribution. This metric reflects the diversity and the complexity of diagonal lines. A high *ENTR* value means complexity is high and a low *ENTR* value means complexity is low. *ENTR* value can be obtained from following formula:

$$ENTR = -\sum_{l=l_{min}}^{N} p\left(l\right) \ln p\left(l\right) \tag{5}$$

In the formula above $p\left(l\right)$ denotes probability of a diagonal line has length l.

LAM (laminarity) quantifies fraction of points in the RP which forms vertical lines. This metric reflects laminar states in the system. A higher *LAM* values mean higher regularity in the system. This measure can detect chaos-chaos transitions. *LAM* value can be calculated by the following formula:

$$LAM = \frac{\sum_{v=v_{min}}^{N} vP\left(v\right)}{\sum_{v=1}^{N} vP\left(v\right)} \tag{6}$$

In the formula above $P\left(v\right)$ denotes frequency distribution of vertical lines with length v.

Vmean is the average length of vertical lines. This metric reflects the average trapping time of the system in particular states. *Vmean* can be calculated by the following formula:

$$Vmean = \frac{\sum_{v=v_{min}}^{N} vP\left(v\right)}{\sum_{v=v_{min}}^{N} P\left(v\right)} \tag{7}$$

Lmean is average length of the diagonal lines. It is the average amount of time that the two segments of the trajectory are in close proximity to one another. It can be considered as average time for forecast. *Lmean* can be calculated by the following formula:

$$Lmean = \frac{\sum_{l=l_{min}}^{N} lP\left(l\right)}{\sum_{l=l_{min}}^{N} P\left(l\right)} \tag{8}$$

APPLICATION AND RESULTS

In this study hourly prices of Bitcoin between dates 17 August 2017 and 5 October 2021 are used. Data is obtained from the cryptocurrency market Binance. In this study also sliding window methodology is adopted. Window size is selected as 1000 and window step size for sliding is selected as 200. The calculations were performed using the *nonlinearTseries* package of the R software.

First step in the analysis of a time series with a RP and RQA is embedding the original univariate time series to obtain multidimensional state vectors. In this procedure a univariate time series such as **x** (9) is converted to multivariate time series such as **V** (10). This procedure is called phase space reconstruction. In this procedure two parameters must be defined. These are embedding dimension (D) and time delay (τ). To determine these parameters, methods such as false nearest neighbors and mutual information are suggested (Huffaker *et al.* 2017).

However, Zbilut (2005) asserted that for economic time series embedding dimension can be selected as 10 and time delay can be selected as 1. In this study we followed Zbilut (2005) suggestion and selected embedding parameters likewise. Percentage of false nearest neighbors graph is presented in Figure 1. From this figure it is seen that after the embedding dimension of 10, percent of false nearest neighbors does not decline much. Therefore, selecting embedding dimension as 10 is an appropriate choice. Average mutual information graph is presented in Figure 2. In the literature it is recommended to choose time delay as the first local minimum of the average mutual information graph. As seen from Figure 2 there is no local minimum. Therefore, by following suggestion of Zbilut (2005) we set time delay as 1 and do not skip any observation. This parameter setting is coherent with the works of Strozzi *et al.* (2007), Strozzi *et al.* (2008), Bastos and Caiado (2011) and Xing and Wang (2020).

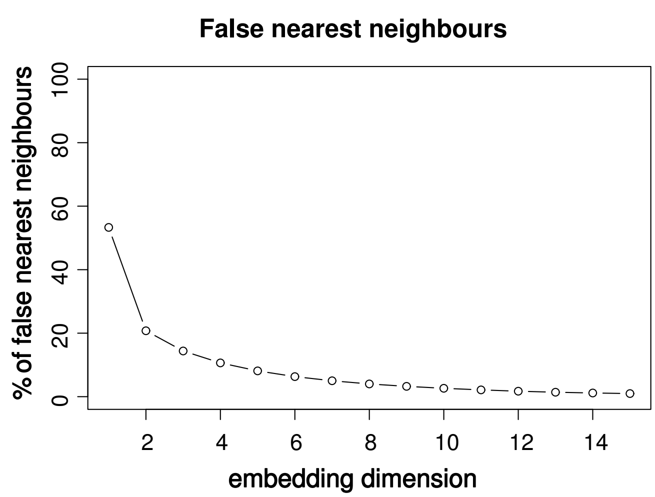

Figure 1 Percentage of false nearest neighbors

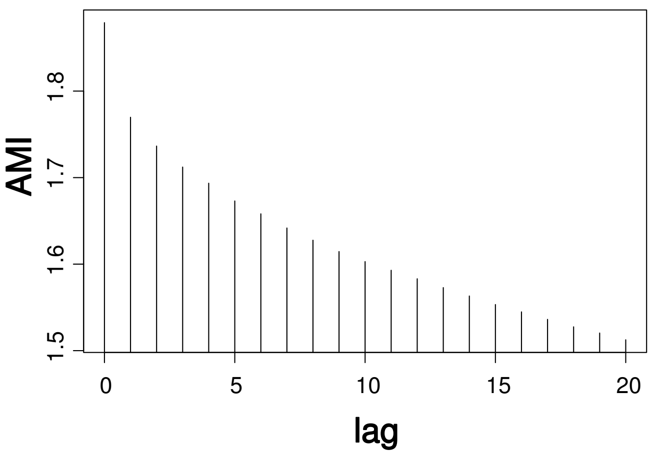

Figure 2 Average mutual information

$$\mathbf{x} = (x_1, x_2, x_3, \ldots, x_n) \tag{9}$$

$$\mathbf{V} = \begin{pmatrix} \mathbf{V}_1 \\ \mathbf{V}_2 \\ \vdots \\ \mathbf{V}_{n-(D-1)\tau} \end{pmatrix} \tag{10}$$

$$\mathbf{V} = \begin{pmatrix} x_1 & x_{1+\tau} & \cdots & x_{1+(D-1)\tau} \\ x_2 & x_{2+\tau} & \cdots & x_{2+(D-1)\tau} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n-(D-1)\tau} & x_{n-(D-2)\tau} & \cdots & x_n \end{pmatrix} \tag{11}$$

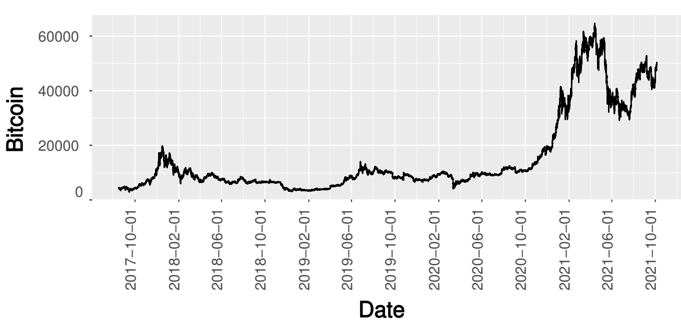

Figure 3 Hourly Bitcoin prices

Graph of hourly Bitcoin prices are presented in Figure 3. As seen from this there is a sharp increase of Bitcoin prices in 2021. Also, Bitcoin prices become more volatile in that time. Changes in the RQA measure recurrence rate (*REC*) through time is presented in Figure 4. As seen from this figure recurrence rate exhibit a fluctuating pattern until 2021. However, in 2021 recurrence rate

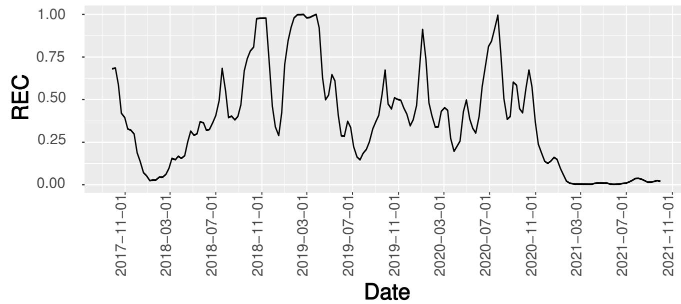

Figure 4 Changes in recurrence rate (REC)

collapse. This means repetitions of the states are significantly reduced in 2021.

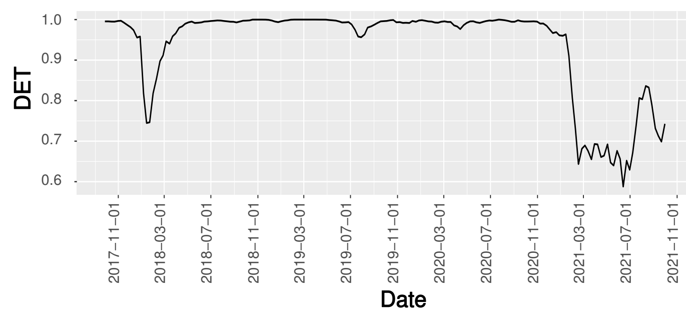

Figure 5 Changes in determinism (DET)

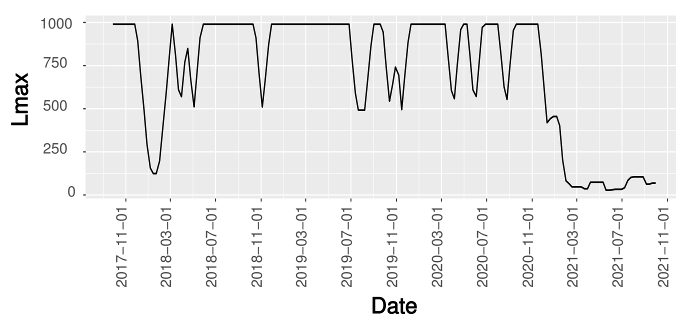

Figure 6 Changes in the longest diagonal line (Lmax)

Changes in the RQA measure determinism (*DET*) through time is depicted in Figure 5. In this figure there is a local dip in determinism in the beginning of the 2018. However more noticeably there is a collapse in determinism in 2021. Since RQA measure determinism reflects the predictability and the randomness of the time series this collapse means Bitcoin becomes more unpredictable and more random in 2021. In the Figure 6 how RQA measure the longest diagonal line (*Lmax*) changes through time is demonstrated. In this Figure until 2021 several local dips are observed. But in 2021 there is a total collapse in Lmax values. Since Lmax reflects the stability of the dynamics and related inversely with largest positive Lyapunov exponent, collapse in 2021 reflects that stability of Bitcoin is significantly reduced in 2021. Changes in the RQA measure laminarity (*LAM*) through time is shown in Figure 7. This figure is similar to the Figure 5 for determinism. In the Figure 7 there is also a local dip in the beginning of the 2018. However, laminarity collapse in 2021 similar to determinism.

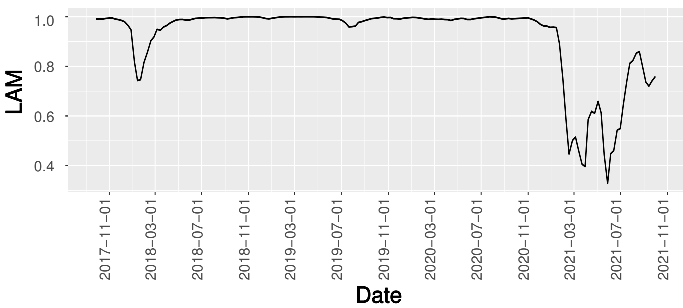

Figure 7 Changes in the laminarity (LAM)

Since RQA measure *LAM* is sensitive to critical changes in the dynamics, collapse in 2021 indicates that dynamics of the Bitcoin is substantially changed and Bitcoin entered a critical state in 2021. Changes in the RQA measure mean length of the diagonal lines (*Lmean*) is presented in Figure 8. This RQA measure gauge the average time for forecast. From this figure it is seen that average time for forecast is greatly reduced in 2021. This again confirms that predictability of the Bitcoin is reduced in 2021.

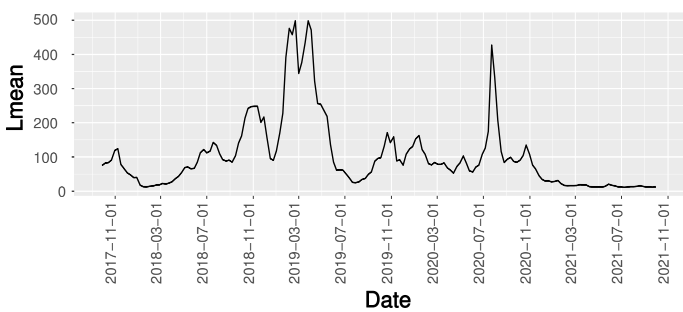

Figure 8 Changes in mean length of the diagonal lines (Lmean)

In Figure 9 changes in the RQA measure average length of vertical lines (*Vmean*) are shown. This RQA measure gauge average trapping time of the system in particular states. From this figure it can be seen that trapping time in particular states are significantly reduced and transitions between states are accelerated in 2021. Changes in the RQA measure Shannon entropy (*ENTR*) is depicted in Figure 10. In this figure it is seen that Shannon entropy is collapsed in 2021. Since Shannon entropy reflects the complexity of the system this collapse reflects that complexity of the Bitcoin is reduced in 2021.

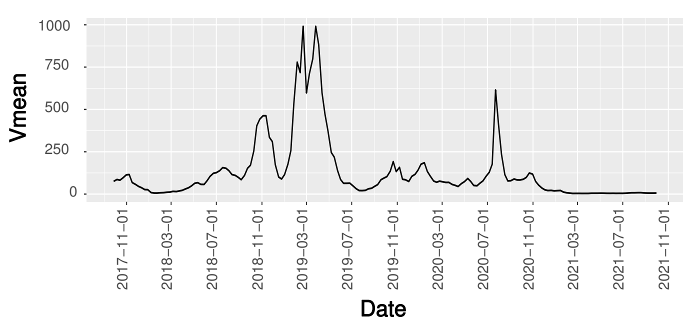

Figure 9 Changes in average length of vertical lines (Vmean)

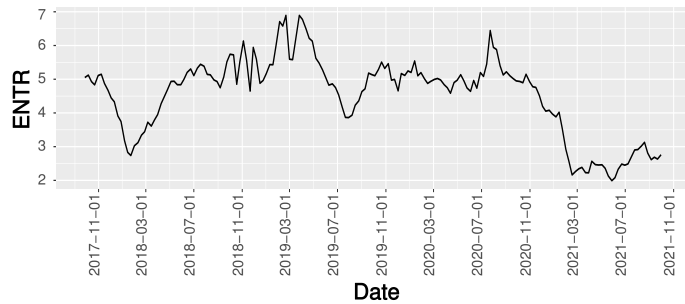

Figure 10 Changes in Shannon entropy (ENTR)

To facilitate ease of comparison, in Figures 11-14 Bitcoin prices and RQA measures are shown on the same graphs. In these figures red curves represents Bitcoin prices and blue curves represents RQA measures. To make a meaningful comparison, Bitcoin prices, *Lmax* and *ENTR* are normalized to the range between 0 and 1. Since *DET* and *LAM* measures take values between 0 and 1, normalization is not required for these variables. As seen from Figures 11-14 the increase in Bitcoin prices is accompanied by a decrease in RQA measures. These graphs reveal that Bitcoin price dynamics are significantly changed in 2021.

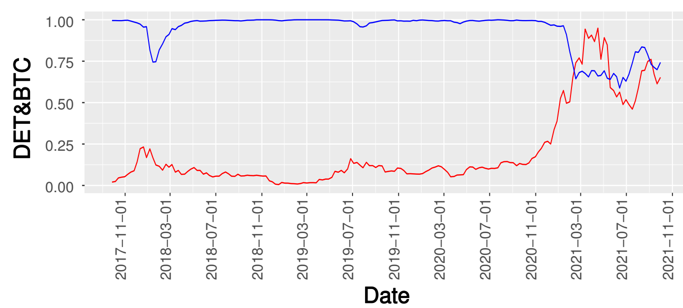

Figure 11 Determinism vs. Bitcoin prices. Red curve denotes Bitcoin prices and blue curve denotes determinism

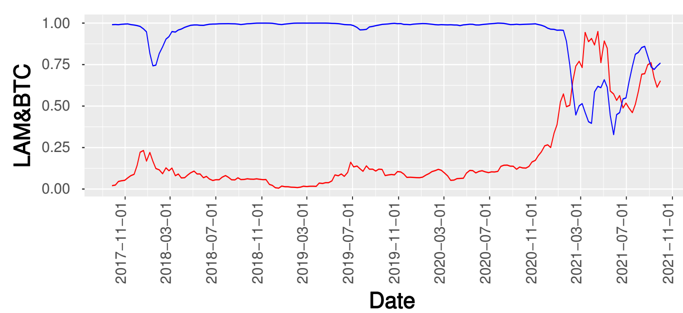

Figure 12 Laminarity vs. Bitcoin prices. Red curve denotes Bitcoin prices and blue curve denotes laminarity

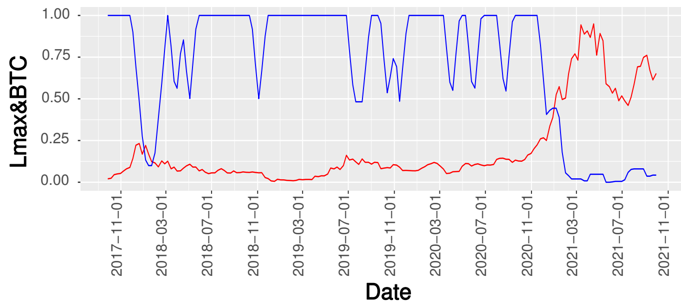

Figure 13 Longest diagonal line's length (Lmax) vs. Bitcoin prices. Red curve denotes Bitcoin prices and blue curve denotes Lmax

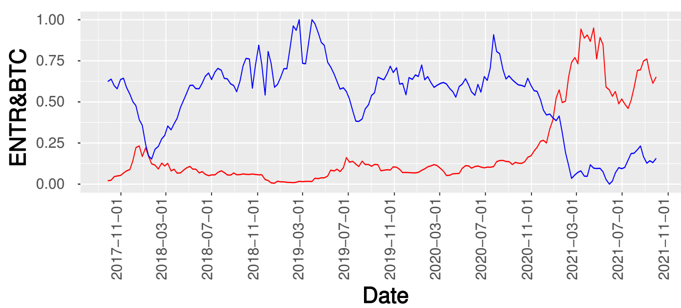

Figure 14 Shannon entropy vs. Bitcoin prices. Red curve denotes Bitcoin prices and blue curve denotes Shannon entropy

CONCLUSION

In this study recurrence quantification analysis is applied to Bitcoin prices to reveal how dynamic properties and stability of Bitcoin prices changed through time. In this analysis change in RQA measures are demonstrated by using sliding window methodology. In the literature it is shown that during or at the beginning of the critical periods such as crisis RQA measures collapse. In this study we demonstrated that RQA measures for Bitcoin prices collapsed in 2021. This means Bitcoin prices become more unpredictable, more random, more unstable, more irregular and less complex in 2021.

Therefore, stability and dynamic characteristics of Bitcoin have been significantly changed in 2021. From this analysis we also can distinguish two different periods for Bitcoin, namely stable and unstable periods. Period before 2021 can be labelled as stable period and period after 2021 can be labelled as unstable period. Therefore, Bitcoin enters a state of turbulence in 2021. From the investors' point of view this means that making investment decisions for Bitcoin becomes much more difficult in 2021. So, what is the reason for this change? Further studies are required to answer this question. Possible explanations can be increase in transaction volumes in the cryptocurrency markets, changes in traders' behaviors, changes in the market conditions and the COVID-19 pandemic.

For traditional currencies when a currency become unstable the corresponding central bank intervenes in the market to stabilize the currency. However, for Bitcoin there is no central bank which decides the amount of emission of the currency. Therefore, since there is no policy maker for Bitcoin, we have no policy implications for Bitcoin. However, we have some implications for investors. Since Bitcoin lost its deterministic structures in 2021 mathematical and statistical models which explain future Bitcoin prices with past realizations become infeasible. Therefore, mathematical models such as difference and differential equations or statistical models such as ARIMA become unsuitable for forecasting future bitcoin prices using past bitcoin prices in 2021. Therefore, investors should consider this situation when creating their investment strategies.

Conflicts of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

Availability of data and material

Not applicable.

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