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Covid-19 impact on cryptocurrencies: Evidence from a wavelet-based Hurst exponent

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ABSTRACT

Cryptocurrency history begins in 2008 as a means of payment proposal. However, cryptocurrencies evolved into a complex ecosystem of high yield speculative assets. Contrary to traditional financial instruments, they are not (mostly) traded in organized, law-abiding venues, but on online platforms, where anonymity reigns. This paper examines the long term memory in return and volatility, using high frequency time series of seven important coins. Our study covers the pre-Covid-19 and the subsequent pandemic period. We use a recently developed method, based on the wavelet transform, which provides more robust estimators of the Hurst exponent. We detect that, during the peak of Covid-19 pandemic (around March 2020), the long memory of returns was only mildly affected. However, volatility suffered a temporary impact in its long range correlation structure. Our results could be of interest for both academics and practitioners.

1. Introduction

Cryptocurrencies have become one of the most traded financial assets in the last decade. In order to put their importance into perspective, two of the most important stock exchanges in the world, the New York Stock Exchange and Nasdaq, report an average of $30 billions and $85 billions in daily volume, respectively. Over the last six months, daily transactions of cryptocurrencies varied between $5 billions and $31 billions, depending on the day. As a consequence, cryptocurrencies have been receiving increasing interest from both academics and practitioners. As a new object of study, it poses several challenges. One of them is to examine the statistical properties of the price generating process. According to the Efficient Market Hypothesis (EMH), the price of any speculative asset must convey all available information [1]. In particular, the weak version of the EMH states that the current price includes all the information contained in the series of past prices. As a consequence of the non-arbitrage possibility, price returns time series should follow a random process with no memory. In particular, it is excluded the possibility of long-term memory, as it could allow for profitable trading strategies.

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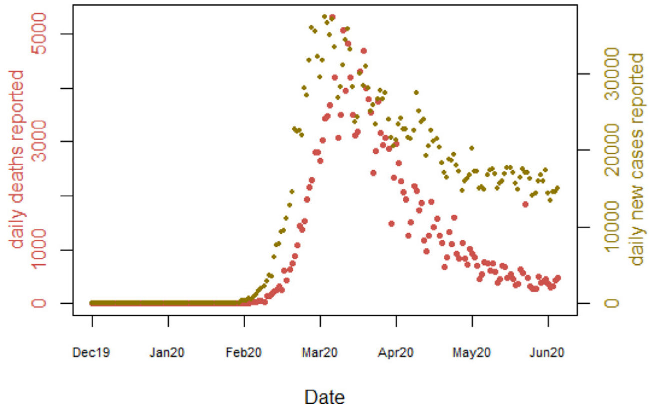

Fig. 1. Number of new cases and deaths reported per day for European countries. Source: European Centre for Disease Prevention and Control [30].

The EMH, specially regarding the presence of long-term memory has been subject to debate since the work by Mandelbrot [2]. It has been extensively studied in developed and emerging stock markets [3–5], in fixed income markets [6–8], interest rates [9–11], and exchange rates [12–14], among other financial time series.

Studies related to cryptocurrencies are much more recent. Specially on these days it is relevant to investigate how markets react to such a global event as Covid-19 pandemic.

Early papers studying the informational efficiency of Bitcoin time series [15,16] find that the returns (and some power transformations) had been informational inefficient, but they also report a trend toward a more efficient behavior. Shortly after these papers, [17] confirms the diminishing memory in daily returns, along with a highly persistent component in daily volatility. Such persistence justifies the use of GARCH-type models in volatility, as proposed by [18,19]. Concurrently, [20] conducts a comprehensive research on Bitcoin time series at 1-min frequency, finding that the stylized facts of the Bitcoin market are becoming closer to mature world markets. Particularly, the authors find compelling evidence of multifractality since the second semester of 2017. On contrary, [21] finds multifractal behavior in the daily returns of Bitcoin, Ethereum, Dash, Litecoin, Monero, Ripple, as early as 2015. The difference between both findings probably is due to the sampling frequencies, making [20] (which uses 1-min data) more precise in determining when the multifractal behavior begins.

For a more detailed description of the current state of cryptocurrency research in economics, we refer to [22], who conduct a comprehensive review and detail the main research lines.

One-time-only events such as a huge price crash or a pandemic, could alter the stochastic process governing returns and volatilities. In this line, [23] finds that before the big price crash of 2013, Bitcoin volatility was asymmetric[2] in the opposite way of the traditional assets, whereas this asymmetry is not found after the price crash. Similarly, a global event such as Covid-19 pandemic, could have non-trivial effects on volatility and returns. Consequently, it begins to be an area of interest for researchers. For example, [24] reports significant growth in both returns and volumes traded in large cryptocurrencies, and [25] affirms that levels of Covid-19 caused a rise in Bitcoin prices.

According to the World Health Organization (WHO) [26], Covid-19 pandemic originates in the People's Republic of China. On December 31st, WHO's country office gathers information issued by the Wuhan Municipal Health Commission reporting cases of 'viral pneumonia'. At the beginning, the virus seemed to be circumscribed to that region. On January 24th. France informed of some cases from people who had been in the Wuhan region, constituting the first confirmed cases in Europe. However, infections and deaths associated to Covid-19 remained at relatively very low levels during January and February. As displayed in Fig. 1, daily number of infected and dead people in Europe rocketed in March, and showed a diminishing trend by the end of that month. Europe has been the first region (after the inception in China) to suffer the pandemic, with its most deadly effect concentrated in a short time frame. In a recent paper, Azimli [27] uses a quantile regression approach to assess the impact Covid-19 on the daily returns of the S&P500 index. Regarding the cryptocurrency market, Drozdz et al. [28] study the effect of Covid-19 on the network topology, using high frequency data from 129 cryptocurrencies. The authors find that there is a shift to a more distributed form, specially on short and medium scales. Additionally, [29] studies daily data of five cryptocurrencies from December 2019 until May 2020, uncovering changes in the multifractal profile of the returns due to Covid-19. Following these lines, we would like to investigate if such a sudden public health problem has had also an impact on the long memory endowment of the cryptocurrency market, from an alternative approach.

The aim of this paper is to study the long memory profiles of return and volatility of seven large cryptocurrencies, during a period spanning before and after the inception of the pandemic event. We contribute to the literature in multiple

2 Asymmetry in volatility means that the reaction of volatility to unexpected positive and negative changes is not the same.

ways: (i) we propose a new method that has not been applied before to compute the Hurst exponent in cryptocurrencies time series; (ii) we study a set of seven important cryptoassets at high frequency; (iii) we compare results obtained at different sampling frequencies; and (iv) we discuss the effect of Covid-19 pandemic on return and volatility.

This remaining of the article is organized as follows: Section 2 presents the methodology used in the paper; Section 3 describes the data used and discusses the empirical findings; and Section 4 concludes.

2. Methods

Harold Edwin Hurst was a British engineer, whose name is intrinsically connected to the study of long range dependence in time series. His original method was presented in a series of papers in the 1950s [31–34]. Although it was originally formulated for the resolution of an specific hydrological problem, it turned out to have more universal applications in the field of time series analysis. The Hurst exponent describes the persistent or anti-persistent character of a time series, arising from its long-range memory.

The presence of long-range memory is compatible with the fractional Brownian motion model postulated in [35,36]. It was precisely Benoit Mandelbrot [37] who proposed in the early 1970s the use of the fractional Brownian motion model in economics [2]. In a series of papers Mandelbrot and coworkers propose a generalization of the standard Brownian motion, which allows for the presence of long memory [35,36,38].

Undoubtedly, finding an accurate measure of long range dependence is a desirable goal in time series analysis. The original R/S method developed by Hurst, has some drawbacks, as it is biased towards finding spurious long memory. This situation triggered the development of alternative methods (e.g. aggregated variance approach [39], Higuchi method [40], Detrended Fluctuation Analysis [41], etc.) to find better estimators for long-range dependence. The review conducted in [42] provides a comprehensive guide for the proper use of the different methods according to the signal characteristics.

Previous works acknowledge that, for an arbitrary artificial time series, the wavelet method does not only find a more accurate H value than the R/S method, but also that it is not necessary to assess *a priori* the series stationarity [42]. Consequently, in this work we use a wavelet-based method to estimate the Hurst exponent.

The continuous wavelet transform allows to decompose the time series in the time–frequency domain, and is defined as:

$$W_{\psi}f(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} f(s)\psi\left(\frac{s-b}{a}\right) ds \quad \text{for} \quad a > 0 \tag{1}$$

where a is the scale parameter, b is the shift parameter and ψ is the mother wavelet. Hereinafter, we will refer to this equation as $W_{a,b}$.

If the time series has $H-$self-affinity, i.e. if the time series satisfies a power law of the kind $X(ct) \approx c^H X(t)$, the variance of the wavelet transform (Eq. (1)) will be asymptotically affected by a scale parameter:

$$Var(a) = \mathbb{E}(W_{a,b})^2 - (\mathbb{E}(W_{a,b}))^2 \approx a^{\beta} \tag{2}$$

where $\beta \in [-1, 3]$. [43] find a relationship between H and β for self-affine series. Consequently, the Hurst exponent is defined as:

- $H = \frac{\beta+1}{2}$, with $\beta \in [-1, 1)$, if the signal is a fGn,
- $H = \frac{\beta-1}{2}$, with $\beta \in [1, 3]$, if the signal is a fBm,

where fBm stands for fractional Brownian motion, and fGn for fractional Gaussian noise.

The wavelet method used in this paper is a modification of the AWC method developed in [44], who propose the following steps:

1. Apply the wavelet transform of the data in the wavelet domain, $W_{a,b}$;
2. Compute, for a fixed scale, a, the average wavelet coefficients;
3. Draw the log–log plot of coefficients vs. scale a.

The key improvement presented in [45] consists in the use of more robust estimators for the computation of the coefficients required in step 2, compared to the estimators used in [44].

Based on Eq. (1), it is proposed to estimate the coefficients of the variance of the time series using two estimators. The first one is the well-known unbiased variance estimator $\widehat{Var}$, which given a set of data $x_1, \ldots, x_m$ is defined as:

$$\widehat{Var}(x) = \frac{1}{m-1}\sum_{i=1}^{m}(x_i - \bar{x})^2 \tag{3}$$

The second one is the median absolute deviation (MAD), which is a more robust estimator of the variance (see [46]):

$$MAD(W_{a,b}) = Med(|W_{a,b} - Med(W_{a,b})|) \tag{4}$$

where $Med(\cdot)$ is the median operator. This improved method will be referred, hereinafter, as AWC-MAD. In [45] AWC-MAD was benchmarked against the classical R/S method and competing alternatives for averaging wavelet coefficients. In all

Table 1
Estimation of the Hurst exponent for fBm and fGn synthetic series, using the AWC-MAD method.

Theoretical H	Estimated H (fBm series)		Estimated H (fGn series)	
	Mean	Std. Dev.	Mean	Std. Dev.
0.2	0.2649	0.0712	0.2602	0.0117
0.4	0.3513	0.0425	0.4097	0.0274
0.6	0.5697	0.0501	0.6044	0.0280
0.8	0.7552	0.0683	0.7898	0.0321

cases AWC-MAD estimations of the Hurst exponent were closer to the theoretical Hurst exponent in synthetic series with 32768 datapoints. Subsequently, [47–49] compare R/S and AWC-MAD methods for climate time series as well as for synthetic time series.

Considering that the main goal of this paper is to study long range dependence in the cryptocurrency market, with shorter time series, we benchmark theoretical and estimated Hurst exponent on fBm and fGn synthetic series with 1435 datapoints. We generate rolling windows of 500 observations, moving forward one observation in each window. The algorithm to generate the artificial series was proposed by [50], and implemented in MatLab with the function `wfbm.m`, using Daubechies wavelet of order 10. Results displayed in Table 1. The first column is the theoretical Hurst exponent value, and the other columns display the mean and standard deviation of the estimations computed on all the rolling windows with the AWC-MAD.

3. Data and empirical results

Cryptocurrencies are traded in online platforms that are not compelled to abide by national financial regulations. Thus, a careful selection of a reliable data source is crucial for the validity of results. We downloaded data from [51]. Bitfinex is one of the largest cryptocurrency exchanges, along with Coinbase and Bitstamp. We downloaded 5, 10, 15 and 20 min data from 14/11/2019 to 08/06/2020. Thus, our analysis begins just before the inception of the pandemic. We present results for data at 20 min frequency, but as will be discussed below, the analysis applies also for the other frequencies. We studied not only continuous returns, but also volatility. Considering that there are several ways of capturing volatility in financial markets, we selected two widely used proxies [52–54]. Additionally, in order to take into account the dynamic character of the market, we compute the Hurst exponents by means of rolling windows. Each rolling window contains data from 15 days. Each window moves two hours forward, keeping constant the quantity of observations. Data covers the period that lies before and after the onset of the Covid-19 pandemic.

Namely, we compute the following measures from the price time series:

- Logarithmic or continuously compounded return:

$$R_t = \log(P_t) - \log(P_{t-1}) \tag{5}$$

  where P_t and P_{t-1} are two consecutive closing prices every two hours.
- Max–min volatility:

$$Vol_t^{max-min} = \log(P_t^{max}) - \log(P_t^{min}) \tag{6}$$

  where P_t^{max} and P_t^{min} the maximum and minimum prices observed in a two-hour period.
- Absolute return volatility:

$$Vol_t^{Abs} = abs(\log(P_t) - \log(P_{t-1})) \tag{7}$$

We obtained important results regarding long memory in returns and in volatility. With respect to returns, as can be appreciated in Fig. 2, the effect of Covid-19 on the Hurst exponent is mild. The average Hurst exponent around 0.5, which is similar to previous findings for time series at low and high frequency sampling [17,55]. Table 2 displays the mean and standard deviations of Hurst exponents, for all windows, windows before 01/03/2020, windows during two weeks in March when there was a peak in the pandemic, and windows after 18/03/2020. We observe that between March 1st. and March 18th. the Hurst exponents are slightly greater than in the preceding period, but they recover previous levels soon after this date. The only exception is EOS that has a more irregular pattern with some peaks in the Hurst exponent in December and late January.

A different picture is obtained when we analyze volatility. There has been a striking effect of Covid-19 on the long-term memory of volatility. This paper uses two proxies for volatility. The first one, is the max–min volatility, and the dynamic evolution of its Hurst exponent is displayed in Fig. 3. Considering that this way of measuring volatility uses the highest and lowest price of a given cryptocurrency within the holding period, it is suitable to capture extreme events.

In Table 3 we observe that the period that goes from November to the early March exhibits very highly persistence (Hurst exponent greater than 0.66). Between March 1st. and March 18th. the Hurst exponents drop suddenly (below Hurst

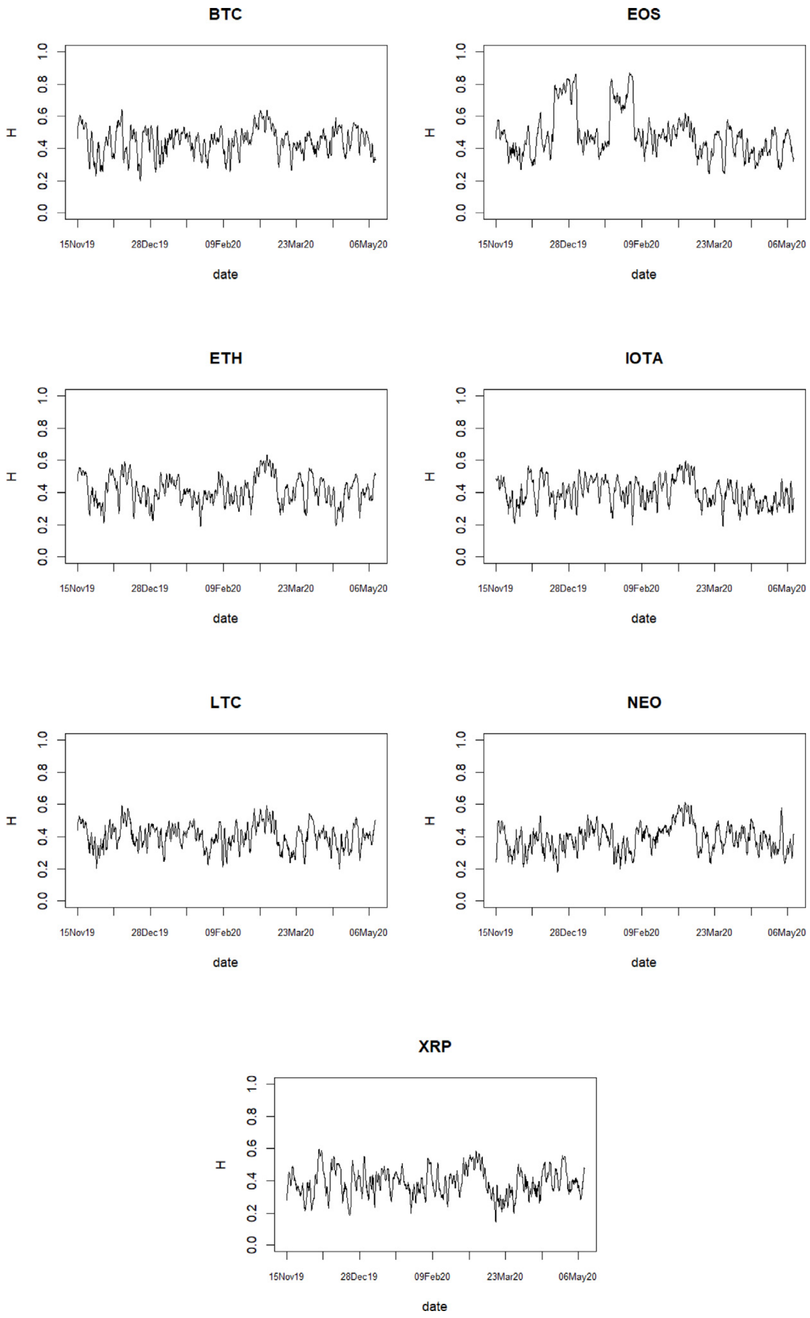

Fig. 2. Hurst exponent of twenty-minute returns, using rolling windows.

0.3 in most cases) and rebound to a even higher level (Hurst exceeding 0.74 in most cases). This situation could reflect a moment of market panic, where large positive returns are followed by large negative returns and vice versa. We should recall that during these days stocks markets around the world were in free fall (for example, the German DAX index plunged by 26%). Cryptocurrencies, as alternative assets, were subject to speculative moves, and those large swings in volatilities could reflect the uncertainty around the true value and feasibility of cryptocurrencies as a safe haven amid the pandemic. After March 18th. the Hurst values reversed to values above 0.67, returning volatility memory to the previous levels.

Absolute returns have been proposed to measure financial time series volatility, and are less sensible than max–min volatility to extreme events. Absolute returns also exhibit a persistent behavior during the periods before and after March.

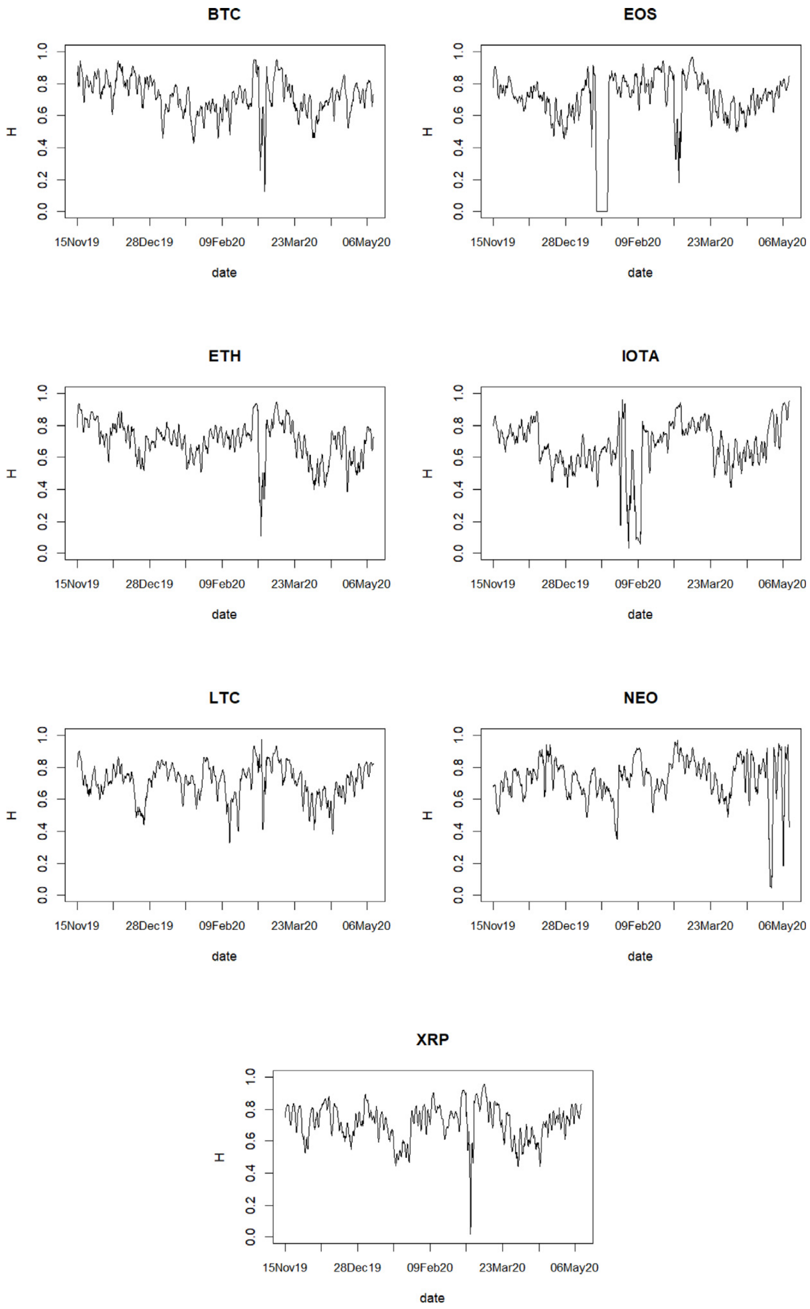

Fig. 3. Hurst exponent of max–min twenty-minute volatility, using rolling windows.

Similarly to max–min volatility, absolute returns increased in their persistence during the upheaval of the Covid-19 crisis (See Fig. 4 and Table 4).

Our findings are relevant for portfolio managers, as risk (proxied by the persistence in volatility) was altered during the peak of the pandemic. Considering that most of the cryptocurrencies studied here exhibits the same pattern, the overall portfolio risk could be compromised.

There is undoubtedly a strong Covid-19 effect on volatility, as both proxies reflect strong changes in their Hurst exponents.

From our sample of seven coins we detect that five of them (BTC, ETH, LTC, NEO, XRP) behave similarly. However, EOS and IOTA seem to follow a different dynamics, confirming the previous finding by [56].

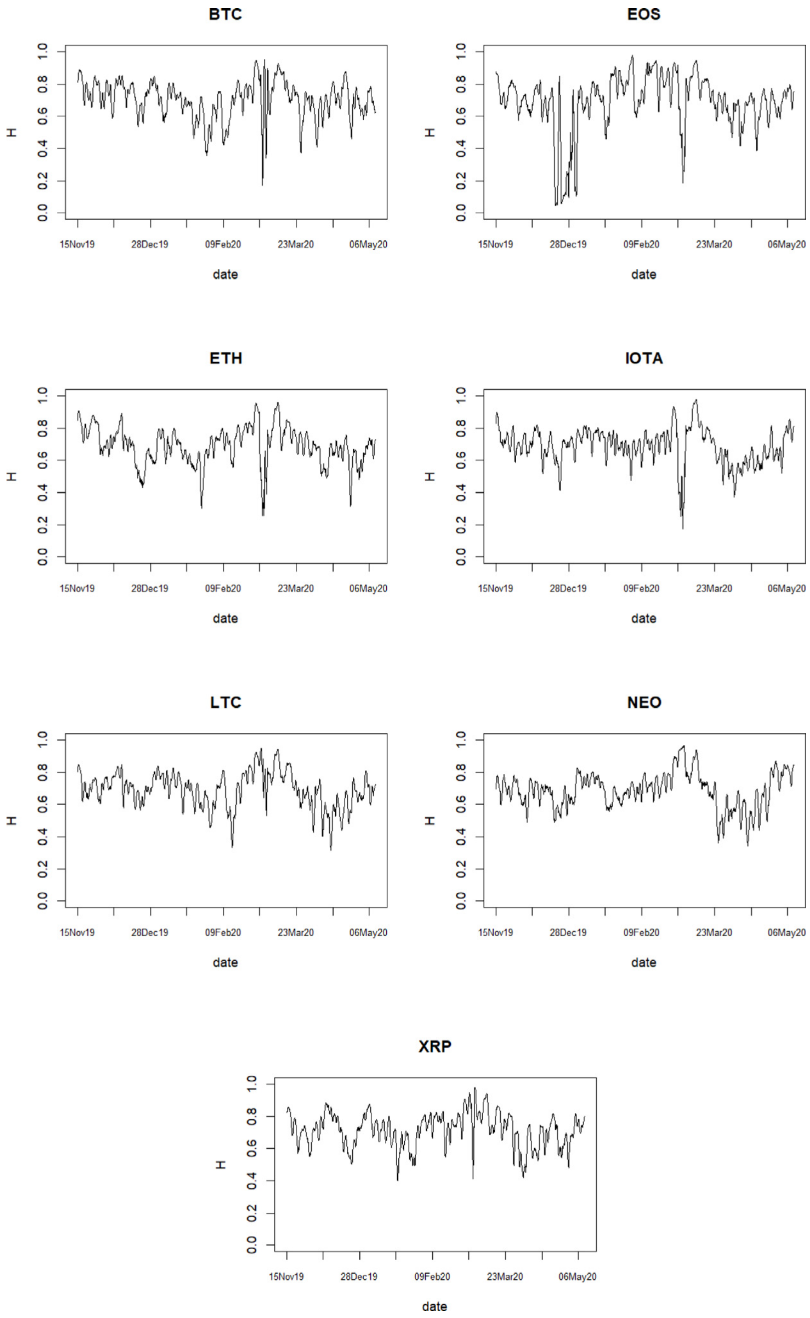

Fig. 4. Hurst exponent of twenty-minute absolute returns, using rolling windows.

In order to provide robustness to our analysis, we also examine the estimates of the Hurst exponents for 5, 10 and 15 min. As can be observed in Figs. 5, 6, and 7 differences are mostly negligible. Unlike Aslan and Sensoy [57], our Hurst estimates are very similar, independently of the sampling frequency selected. For brevity, we do not include the results of the other cryptocurrencies at higher frequencies, but results are similar to those presented for Bitcoin. As a caveat, smaller cryptocurrencies could suffer from infrequent trading, making difficult to find data of higher granularity.

Finally, in order to examine in time frequency the relationship between Covid-19 and the Hurst exponents, we perform a wavelet coherence analysis. We apply the methodology developed by Grinsted et al. [58].

We compute the coherence analysis between the different Hurst exponents calculated before, and Covid-19 cases and deaths. For the sake of brevity, we present only the results regarding the Hurst exponents of absolute returns and Covid-19 cases, as the analysis of the other series give similar results. Fig. 8 clearly shows that the largest impact in the

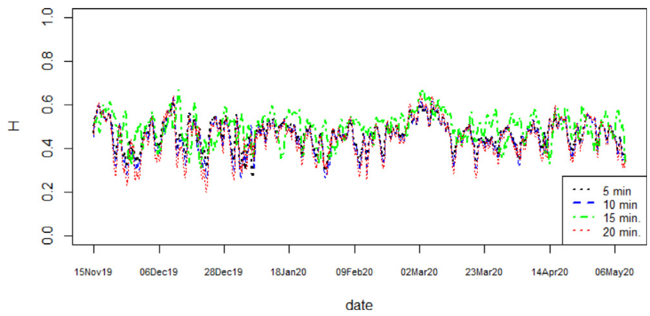

Fig. 5. Hurst exponent of Bitcoin returns at 5, 10, 15, and 20-minute frequency.

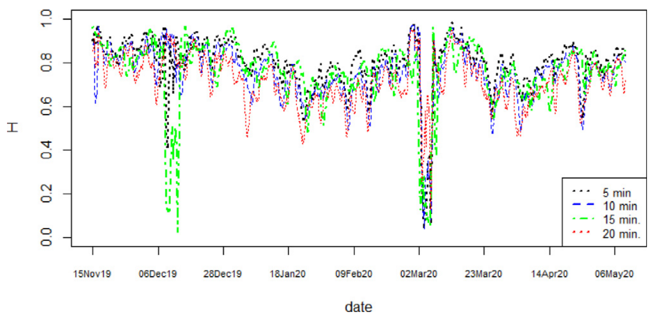

Fig. 6. Hurst exponent of Bitcoin max–min volatility at 5, 10, 15, and 20-minute frequency.

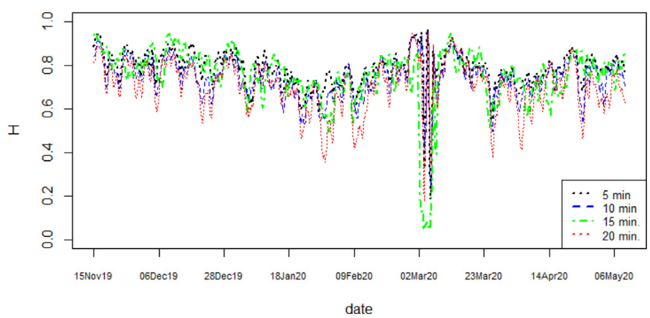

Fig. 7. Hurst exponent of Bitcoin absolute returns at 5, 10, 15, and 20-minute frequency.

Table 2
Mean and standard deviations of Hurst exponent of return time series. Results are presented for all windows: before 01/03/2020, between 01/03/2020 and 18/03/2020, and after 18/03/2020.

Currency	Hurst exponent of 20 min. returns							
	Whole period		Before March 1st.		1st.–18th. March		After March 18th.	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
BTC	0.44418	0.11984	0.42888	0.13097	0.49322	0.09830	0.44042	0.10214
EOS	0.48747	0.15885	0.53554	0.17824	0.47804	0.09965	0.40750	0.11274
ETH	0.41561	0.11685	0.41028	0.11717	0.44859	0.12267	0.40423	0.10867
IOTA	0.40341	0.11987	0.40885	0.11717	0.45507	0.11455	0.36091	0.11312
LTC	0.40374	0.11590	0.40373	0.11822	0.42888	0.11267	0.38780	0.11096
NEO	0.38893	0.12461	0.37117	0.12336	0.45774	0.12317	0.37702	0.11244
XRP	0.38963	0.12976	0.38789	0.12717	0.41413	0.12883	0.37718	0.13300

evolution of the Hurst exponent was contemporaneous to the worst period of the pandemic. In particular we observe that when the slope of Covid-19 cases became steeper in March 15th. (around day 70 of the figure), there is an abrupt impact on Hurst estimates. This situation is captured by the wavelet coherence displayed in Fig. 9. In fact, we observe lack of coherence between the two signals during the first fifty days of year 2020, as could be expected. However, around

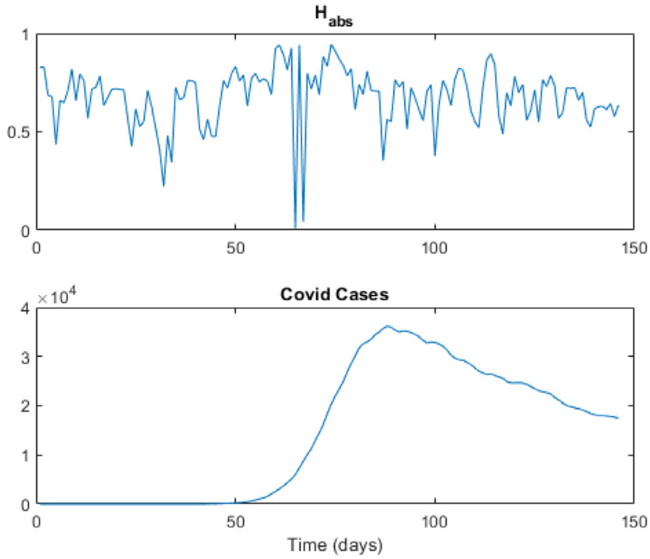

Fig. 8. Hurst exponent of Bitcoin absolute returns (upper panel) and Covid-19 cases.

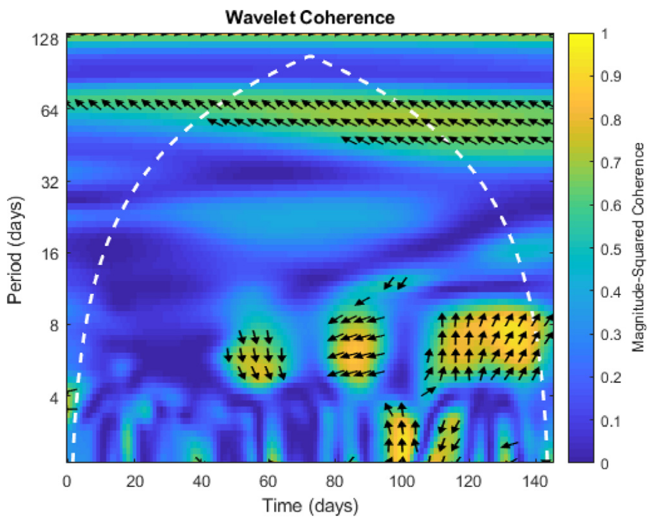

Fig. 9. Wavelet coherence of Hurst exponent of Bitcoin absolute returns and Covid-19 cases.

Table 3
Mean and standard deviations of Hurst exponent of max–min volatility. Results are presented for all windows: before 01/03/2020, windows 01/03/2020 and 18/03/2020, and after 18/03/2020.

Currency	Hurst exponent of 20 min. max–min volatility							
	Whole period		Before March 1st.		1st.–18th. March		After March 18th.	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
BTC	0.71866	0.15058	0.72701	0.13294	0.74238	0.22872	0.68866	0.10732
EOS	0.69735	0.21022	0.66974	0.23329	0.79045	0.23710	0.68765	0.10694
ETH	0.70276	0.15227	0.72578	0.10578	0.74542	0.23138	0.63450	0.13679
IOTA	0.67333	0.19392	0.62702	0.22405	0.77154	0.09925	0.69383	0.14965
LTC	0.71169	0.13781	0.71300	0.11334	0.76158	0.19303	0.67768	0.12540
NEO	0.72973	0.17469	0.72058	0.13406	0.78059	0.12037	0.71382	0.24734
XRP	0.71519	0.14334	0.71693	0.11830	0.75996	0.21584	0.68367	0.11642

mid March, Covid-19 cases affected the long memory dynamics of Bitcoin absolute returns. Most of the coherence is in the frequency of 4 to 8 days, except around day 100, which corresponds to mid April. We should remember that during

Table 4
Mean and standard deviations of Hurst exponent of absolute returns time series. Results are presented for all windows: before 01/03/2020, between 01/03/2020 and 18/03/2020, and after 18/03/2020.

Currency	Hurst exponent of 20 min. absolute returns							
	Whole period		Before March 1st.		1st.–18th. March		After March 18th.	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
BTC	0.70423	0.14148	0.69474	0.12507	0.76918	0.19478	0.67998	0.11451
EOS	0.68853	0.21650	0.66699	0.24426	0.78912	0.22871	0.66320	0.11306
ETH	0.69129	0.14934	0.68759	0.12349	0.75691	0.22816	0.65626	0.11019
IOTA	0.68881	0.14311	0.70372	0.09521	0.73187	0.23601	0.63482	0.11896
LTC	0.69214	0.13510	0.69402	0.10437	0.78307	0.17091	0.63105	0.12463
NEO	0.68887	0.12592	0.68140	0.08971	0.79470	0.10512	0.63508	0.15102
XRP	0.71407	0.12856	0.71131	0.10851	0.78435	0.15519	0.67441	0.12477

at the beginning of April, the first peak of the pandemic was reached and hard policy measures were enforced in many countries (stay-at-home orders, travel restrictions, public meetings restrictions, etc.). Then, the coherence between both signals became more immediate, becoming significant at a frequency between 1 to 4 days. After that, and until the end of our data, the wavelet coherence is significant at 4–8 days frequency.

4. Conclusions

This paper's contribution is multiple. Firstly, it applies a new, improved, wavelet-based method to compute the Hurst exponent. Secondly, it provides an analysis of high frequency returns and volatility of seven cryptocurrencies during Covid-19 pandemic. Thirdly, we analyze time series at different sampling frequency (5 to 20 min), being results essentially similar independently of data granularity. We find that, even though the ongoing pandemic has produced only a mild effect on the long-range memory of cryptocurrency returns, it imprinted a strong transitory effect on volatility. We use two alternative measures of return volatility: max–min and absolute returns. Both proxies reflect a significant change in their long memory profile. There is a momentary drop and subsequent rebound in long memory around the peak of the pandemic. The Hurst exponent of both volatility proxies return to levels previous to the Covid-19 pandemic, after March 18th. until the end of the sample (June 2020). Thus, we conclude that this one-time-only event has had only a transitory effect on the long memory profile of returns and volatilities. By means of the wavelet coherence analysis we also detect that the incidence of Covid-19 on the long memory dynamics (mostly at a 4 to 8 days frequency) begins in March.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Eugene F. Fama, Efficient capital markets: A review of theory and empirical work, J. Finance 25 (1970) 383–417, 2, Papers and Proceedings of the Twenty-Eighth Annual Meeting of the American Finance Association New York, N.Y. December, 28-30, 1969.
[2] Benoit Mandelbrot, The variation of certain speculative prices, J. Bus. 36 (4) (1963) 394–419.
[3] John T. Barkoulas, Christopher F. Baum, Long-term dependence in stock returns, Econom. Lett. 53 (3) (1996) 253–259.
[4] Epaminondas Panas, Estimating fractal dimension using stable distributions and exploring long memory through ARFIMA models in Athens Stock Exchange, Appl. Financial Econ. 11 (4) (2001) 395–402, http://www.informaworld.com/10.1080/096031001300313956.
[5] Daniel O. Cajueiro, Benjamin M. Tabak, Possible causes of long-range dependence in the Brazilian stock market, Physica A: Stat. Mech. Appl. 345 (3-4) (2005) 635–645.
[6] A. Carbone, G. Castelli, H.E. Stanley, Time-dependent Hurst exponent in financial time series, Physica A: Stat. Mech. Appl. 344 (1-2) (2004) 267–271.
[7] Aurelio F. Bariviera, M. Belén Guercio, Lisana B. Martinez, A comparative analysis of the informational efficiency of the fixed income market in seven European countries, Econom. Lett. 116 (3) (2012) 426–428, http://dx.doi.org/10.1016/j.econlet.2012.04.047.
[8] A.F. Bariviera, M. Belén Guercio, Lisana B. Martinez, Informational efficiency in distressed markets: The case of european corporate bonds, Econ. Soc. Rev. 45 (3) (2014) 349–369.
[9] Matthieu Garcin, Estimation of time-dependent Hurst exponents with variational smoothing and application to forecasting foreign exchange rates, Physica A: Stat. Mech. Appl. 483 (2017) 462–479, http://dx.doi.org/10.1016/j.physa.2017.04.122, http://www.sciencedirect.com/science/article/pii/S037843711730434X.
[10] A. Sensoy, Effects of monetary policy on the long memory in interest rates: Evidence from an emerging market, Chaos Solitons Fractals 57 (2013) 85–88, http://dx.doi.org/10.1016/j.chaos.2013.09.002, http://www.sciencedirect.com/science/article/pii/S0960077913001793.
[11] Daniel O. Cajueiro, Benjamin M. Tabak, Fluctuation dynamics in US interest rates and the role of monetary policy, Finance Res. Lett. 7 (3) (2010) 163–169, http://dx.doi.org/10.1016/j.frl.2010.03.001.
[12] Raul Matsushita, Iram Gleria, Annibal Figueiredo, Sergio Da Silva, Are pound and euro the same currency? Phys. Lett. A 368 (3-4) (2007) 173–180.
[13] Sergio R.S. Souza, Benjamin M. Tabak, Daniel O. Cajueiro, Long-range dependence in exchange rates: The case of the european monetary system, Int. J. Theor. Appl. Finance (IJTAF) 11 (02) (2008) 199–223, http://dx.doi.org/10.1142/S0219024908004774.

[14] Yan-Hong Yang, Ying-Hui Shao, Hao-Lin Shao, H. Eugene Stanley, Revisiting the weak-form efficiency of the EUR/CHF exchange rate market: Evidence from episodes of different Swiss franc regimes, Physica A: Stat. Mech. Appl. 523 (2019) 734–746, http://dx.doi.org/10.1016/j.physa.2019.02.056.
[15] Andrew Urquhart, The inefficiency of Bitcoin, Econom. Lett. 148 (2016) 80–82, http://dx.doi.org/10.1016/j.econlet.2016.09.019.
[16] Saralees Nadarajah, Jeffrey Chu, On the inefficiency of Bitcoin, Econom. Lett. 150 (2017) 6–9, http://dx.doi.org/10.1016/j.econlet.2016.10.033.
[17] Aurelio F. Bariviera, The inefficiency of Bitcoin revisited: A dynamic approach, Econom. Lett. 161 (2017) 1–4, http://dx.doi.org/10.1016/j.econlet.2017.09.013.
[18] Paraskevi Katsiampa, Volatility estimation for Bitcoin: A comparison of GARCH models, Econom. Lett. 158 (2017) 3–6, http://dx.doi.org/10.1016/j.econlet.2017.06.023, http://www.sciencedirect.com/science/article/pii/S0165176517302501.
[19] Paraskevi Katsiampa, Volatility co-movement between Bitcoin and Ether, Finance Res. Lett. 30 (2019) 221–227, http://dx.doi.org/10.1016/j.frl.2018.10.005, http://www.sciencedirect.com/science/article/pii/S1544612318305580.
[20] Stanisław Drożdż, Robert Gebarowski, Ludovico Minati, Paweł Oświecimka, Marcin Watorek, Bitcoin market route to maturity? Evidence from return fluctuations, temporal correlations and multiscaling effects, Chaos 28 (7) (2018) 071101, http://dx.doi.org/10.1063/1.5036517.
[21] Khamis Hamed Al-Yahyaee, Walid Mensi, Hee Un Ko, Seong Min Yoon, Sang Hoon Kang, Why cryptocurrency markets are inefficient: The impact of liquidity and volatility, North Am. J. Econ. Finance 52 (March) (2020) 101168, http://dx.doi.org/10.1016/j.najef.2020.101168.
[22] Aurelio F. Bariviera, Ignasi Merediz-Solà, Where do we stand in cryptocurrencies economic research? A survey based on hybrid analysis, J. Econ. Surv. 35 (2) (2021) 377–407, http://dx.doi.org/10.1111/joes.12412, arXiv:2003.09723.
[23] Elie Bouri, Georges Azzi, Anne Haubo Dyhrberg, On the return-volatility relationship in the Bitcoin market around the price crash of 2013, Econom. Open-Access Open-Assessment E-J. 11 (2017) 1–16, http://dx.doi.org/10.5018/economics-ejournal.ja.2017-2.
[24] S. Corbet, Y.G. Hou, Y. Hu, C. Larkin, L. Oxley, Any port in a storm: Cryptocurrency safe-havens during the COVID-19 pandemic, Econom. Lett. 194 (2020) http://dx.doi.org/10.1016/j.econlet.2020.109377.
[25] J.W. Goodell, S. Goutte, Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis, Finance Res. Lett. (2020) http://dx.doi.org/10.1016/j.frl.2020.101625.
[26] World Health Organization, Timeline: WHO's COVID-19 response, 2020, https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline#event-74. (Accessed 9 September 2020).
[27] Asil Azimli, The impact of COVID-19 on the degree of dependence and structure of risk-return relationship: A quantile regression approach, Finance Res. Lett. 36 (April) (2020) 101648, http://dx.doi.org/10.1016/j.frl.2020.101648.
[28] Stanisław Drozdz, Jarosław Kwapień, Paweł Oświecimka, Tomasz Stanisz, Marcin Watorek, Complexity in economic and social systems: Cryptocurrency market at around COVID-19, Entropy 22 (9) (2020) 1–25, http://dx.doi.org/10.3390/E22091043.
[29] Emna Mnif, Anis Jarboui, Khaireddine Mouakhar, How the cryptocurrency market has performed during COVID 19? A multifractal analysis, Finance Res. Lett. 36 (June) (2020) 101647, http://dx.doi.org/10.1016/j.frl.2020.101647.
[30] European Centre for Disease Prevention and Control, Daily update of new reported cases of COVID-19 by country worldwide, 2020, https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide. (Accessed 9 September 2020).
[31] H.E. Hurst, Long-term storage capacity of reservoirs, Trans. Am. Soc. Civ. Eng. 116 (1951) 770–808.
[32] H.E. Hurst, Methods of usign long-term storage in reservoirs, Proc. Inst. Civ. Eng. 1 (1956) 519–543.
[33] H.E. Hurst, The problem of long-term storage in reservoirs, Int. Assoc. Sci. Hydrol. Bull. 1 (3) (1956) 13–27, http://dx.doi.org/10.1080/02626665609493644.
[34] Harold Edwin Hurst, A suggested statistical model of some time series which occur in nature, Nature 180 (4584) (1957) 494, http://dx.doi.org/10.1038/180494a0.
[35] Benoit B. Mandelbrot, John W. Van Ness, Fractional brownian motions, fractional noises and applications, SIAM Rev. 10 (4) (1968) 422–437.
[36] Benoit B. Mandelbrot, James R. Wallis, Noah, Joseph, and operational hydrology, Water Resour. Res. 4 (5) (1968) 909–918.
[37] Benoit B. Mandelbrot, Statistical methodology for nonperiodic cycles: From the covariance to Rs analysis, in: Annals of Economic and Social Measurement, Volume 1, number 3, in: NBER Chapters, National Bureau of Economic Research, 1972, pp. 259–290.
[38] Benoit B. Mandelbrot, James R. Wallis, Computer experiments with fractional Gaussian Noises: Part 2, rescaled ranges and spectra, Water Resour. Res. 5 (1) (1969) 242–259, http://dx.doi.org/10.1029/WR005i001p00242.
[39] Jan Beran, A test of location for data with slowly decaying serial correlations, Biometrika 76 (2) (1989) 261–269, http://www.jstor.org/stable/2336659.
[40] T. Higuchi, Approach to an irregular time series on the basis of the fractal theory, Phys. D. Nonlinear Phenom. 31 (2) (1988) 277–283, http://dx.doi.org/10.1016/0167-2789(88)90081-4, http://www.sciencedirect.com/science/article/pii/0167278988900814.
[41] CK Peng, SV Buldyrev, S Havlin, M Simons, HE Stanley, AL Goldberger, Mosaic organization of DNA nucleotides, Phys. Rev. E. Stat. Phys. Plasmas Fluids Related Interdiscip. Top. 49 (2) (1994) 1685–1689, http://dx.doi.org/10.1103/physreve.49.1685, http://www.ncbi.nlm.nih.gov/pubmed/9961383.
[42] Francesco Serinaldi, Use and misuse of some Hurst parameter estimators applied to stationary and non-stationary financial time series, Physica A: Stat. Mech. Appl. 389 (14) (2010) 2770–2781, http://dx.doi.org/10.1016/j.physa.2010.02.044, http://www.sciencedirect.com/science/article/pii/S0378437110001718.
[43] B.D. Malamud, D.L. Turcotte, Self-affine time series: measures of weak and strong persistence, J. Stat. Plan. Inference 80 (1999) 173–196, http://dx.doi.org/10.1016/S0378-3758(98)00249-3, http://www.sciencedirect.com/science/article/pii/S0378375898002493.
[44] I. Simonsen, A. Hansen, O. Nes, Determination of the Hurst exponent by use of wavelet transforms, Phys. Rev. E 58 (1998) 2779.
[45] M.B. Arouxet, V.E. Pastor, Estudio del exponente de Hurst, Mecánica Comput. 35 (2017) 2501–2508, https://amcaonline.org.ar/ojs/index.php/mc/article/view/5464/5437.
[46] R.A. Maronna, R.D. Martin, V.J. Yohai, Robust statistics: Theory and methods, Robust Statistics, John Wiley & Sons, Ltd, 2006, pp. 397–403, http://dx.doi.org/10.1002/0470010940, http://dx.doi.org/10.1002/0470010940.
[47] M.B. Arouxet, V.E. Pastor, Caracterización de series climáticas usando el exponente de Hurst, Mecánica Comput. 36 (2018) 411–419, https://cimec.org.ar/~mstorti/MECOM2018/paper-5719.pdf.
[48] M.B. Arouxet, V.E. Pastor, Un estudio de series de precipitaciones usando la transoformada Wavelet, in: VII Congreso de Matemática Aplicada, Computacional e Industrial - MACI 2019, 2019, pp. 411–419, https://amcaonline.org.ar/maci/index.php/maci2019/maci/paper/viewFile/5111/503.
[49] M.B. Arouxet, V.E. Pastor, V. Vampa, Using the Wavelet Transform for time series analysis, in: J.P. Muszkats, S.A. Seminara, M.I. Troparevsky (Eds.), Applications of Multiresolution Analysis with wavelets, SEMA SIMAI Springer Series, 4, Springer International Publishing, Cham, 2021, pp. 59–74, http://dx.doi.org/10.1007/978-3-030-61713-4_4.
[50] P. Abry, F. Sellan, The wavelet-based synthesis for the fractional Brownian motion proposed by F. Sellan and Y. Meyer: Remarks and fast implementation, Appl. and Comp. Harmonic Anal. 4 (1996) 377–383.
[51] bitfinex, The home of digital asset trading, 2020, https://www.bitfinex.com/. (Accessed 10 November 2020).
[52] A. Ronald Gallant, Chien Te Hsu, George Tauchen, Using daily range data to calibrate volatility diffusions and extract the forward integrated variance, Rev. Econ. Stat. 81 (4) (1999) 617–631, http://dx.doi.org/10.1162/003465399558481.

[53] Sassan Alizadeh, Michael W. Brandt, Francis X. Diebold, Range-based estimation of stochastic volatility models, J. Finance 57 (3) (2002) 1047–1091, http://dx.doi.org/10.1111/1540-6261.00454.
[54] John Cotter, Absolute return volatility, SSRN Electron. J. (2011) http://dx.doi.org/10.2139/ssrn.998770.
[55] Aurelio F. Bariviera, One model is not enough: heterogeneity in cryptocurrencies' multifractal profiles, Finance Res. Lett. 39 (101649) (2021) http://dx.doi.org/10.1016/j.frl.2020.101649.
[56] Aurelio F. Bariviera, Luciano Zunino, Osvaldo A. Rosso, An analysis of high-frequency cryptocurrencies prices dynamics using permutation-information-theory quantifiers, Chaos 28 (7) (2018) 075511, http://dx.doi.org/10.1063/1.5027153.
[57] Aylin Aslan, Ahmet Sensoy, Intraday efficiency-frequency nexus in the cryptocurrency markets, Finance Res. Lett. 35 (August 2019) (2020) 101298, http://dx.doi.org/10.1016/j.frl.2019.09.013.
[58] A. Grinsted, J.C. Moore, S. Jevrejeva, Application of the cross wavelet transform and wavelet coherence to geophysical time series, Nonlinear Process. Geophys. 11 (5/6) (2004) 561–566, http://dx.doi.org/10.5194/npg-11-561-2004, https://npg.copernicus.org/articles/11/561/2004/.