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The effect of COVID-19 on long memory in returns and volatility of cryptocurrency and stock markets

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ABSTRACT

We examine long memory (self-similarity) in digital currencies and international stock exchanges prior and during COVID-19 pandemic. Specifically, ARFIMA and FIGARCH models are respectively employed to evaluate long memory parameter in returns and volatility. The dataset contains 45 cryptocurrency markets and 16 international equity markets. The *t*-test and F-test are performed to estimated long memory parameters. The empirical findings follow. First, the level of persistence in return series of both markets has increased during the COVID-19 pandemic. Second, during COVID-19 pandemic, variability level in persistence in return series has increased in both digital currencies and stock markets. Third, return series in both markets exhibited comparable level of persistence prior and during the COVID-19 pandemic. Fourth, return series in volatility series of cryptocurrency exhibited high degree of persistence compared to international stock markets during the COVID-19 pandemic. Therefore, it is concluded that COVID-19 pandemic significantly affected long memory in return and volatility of cryptocurrency and international stock markets. In addition, our results suggest that the hybrid long memory model represented by the integration of ARFIMA-FIGARCH is significantly suitable to describe returns and volatility of cryptocurrencies and stocks and to reveal differences before and during COVID-19 pandemic periods.

1. Introduction

Time series exhibiting long memory (self-similarity) are stationary processes that have statistical long-range dependency between contemporary and past values in different times of the series. By the way, presence of long memory suggests that dynamics in data are affected by historical fluctuations for long time and with dependency consequences [1,2]. The long-memory characteristic in asset return and volatility is a fascinating topic for scholars and investors since appropriate return and volatility modelling is crucial for asset allocation and risk control. For instance, existence of long memory in asset returns indicates that historical price changes could be predictors of future price changes. Similarly, volatility process showing presence of long memory suggests that past volatility could be employed to forecast imminent volatility.

Therefore, in the last decade, numerous studies have been conducted on presence of long memory in equity markets. For instance, it was examined in stock markets [3-6], commodity markets [7-13], cryptocurrency markets [14-21], and in alternative investments [22,23]. Besides, other studies examined long memory in volatility series of stock markets [24-27], commodity markets [28-34], cryptocurrency markets [35-38], and in alternative investments [27]. These previous works concluded that long memory widely existed in the returns of international stock, cryptocurrency, commodity, and alternative investments [3-23], and also their respective volatilities [24-36]. In other words, returns and volatilities in such diverse investments showed strong evidence of nonlinear dependence in the moments of the distribution; hence, an opportunity to forecast data fluctuations.

However, thus far, it is needed to investigate presence of long memory in cryptocurrency and international stock markets during the current COVID-19 pandemic. Hence, the current study enriches the literature by estimating long memory parameter in return and volatility time series of digital currencies and international equity markets separately before and during COVID-19 pandemic. Truly, our research on long memory is important because it (1) establishes a reference study on the impact of COVID-19 pandemic on long memory of returns and volatilities of digital currencies and standard stocks, (2) provides suitable information for asset allocation and portfolio management during COVID-19 pandemic, and

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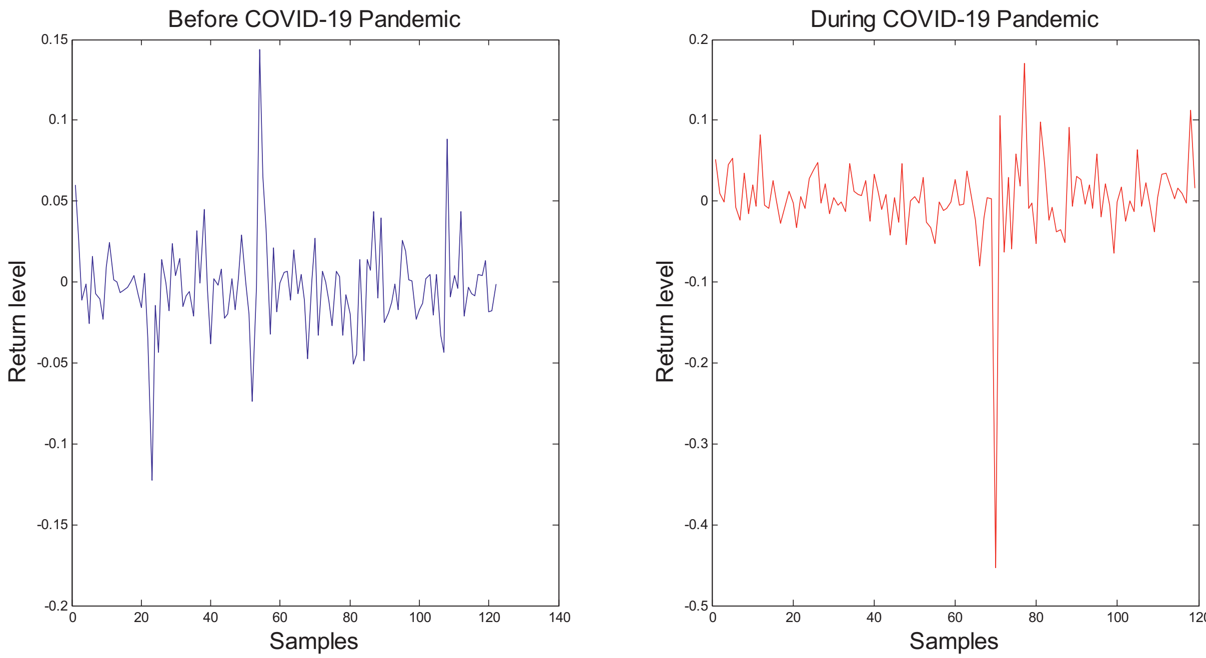

Fig. 1. Returns of Bitcoin prior and throughout COVID-19 pandemic.

(3) distinguishes cryptocurrency markets from international stock markets.

To this end, we use the autoregressive fractionally integrated moving average (ARFIMA) [37,38] and the fractionally integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) [39] models to respectively estimate long memory (self-similarity) in return and volatility time series, and we base our analysis on distinct two periods; the first one, preceding COVID-19 pandemic, and the second one, throughout the COVID-19 pandemic.

The autoregressive fractionally integrated moving average (ARFIMA) model [21,22] is a parametric and parsimonious model to evaluate long memory in time series. Hence, ARFIMA overcomes the limited ability of standard ARMA process in incorporating long-range correlations. Indeed, the mostly prominent merit of the ARFIMA specification is that it permits short- and long-term dependencies to be disjointedly analysed. Besides, the FIGARCH model [39] is a flexible process convenient to incorporate volatility clustering and measure time-variation and long-range memory in a signal. Both ARIMA and FIGARCH processes are popular in examination of asset return and volatility respectively as they afford efficient long memory estimates.

In sum, the contributions of our study follow. First, we investigate the effect of COVID-19 pandemic on long memory of cryptocurrency and internationals stock markets. In this regard, we integrate ARFIMA and FIGARCH in one single model to obtain ARFIMA-FIGARCH model. Second, we examine long memory in cryptocurrency and in internationals stock markets and check for differences between these two attractive categories of markets. Third, a large dataset composed of 61 market is considered. Fourth, we enrich existing literature dealing with effect of the COVID-19 pandemic on asset markets [40-46]. Surely, our results would help investors setting appropriate asset allocation and trading strategies so as to increase profits.

The remaining our study follows: Section 2 introduces ARFIMA and FIGARCH processes. Section 3 describes data and provides empirical results. Finally, we conclude in Section 4.

2. Methods

The ARFIMA model [37,38] is a parametric and parsimonious process to capture long memory in stationary time series such as asset returns. Besides, The FIGARCH model [39] represents a flexible statistical approach to account for volatility clustering and to measure long memory in volatility of returns. In the current study, we specify the ARFIMA(p_m, d_m, p_m)-FIGARCH(p_v, d_v, p_v) model as:

$$\phi(L)(1-L)^{d_m}(r_t-\mu)=\beta(L)\varepsilon_t \tag{1}$$

$$\varepsilon_t=\eta_t\sqrt{h_t} \tag{2}$$

$$\alpha(L)(1-L)^{d_v}\varepsilon_t^2=\omega+(1-\theta(L))\nu_t \tag{3}$$

Following the mathematical expression above, the twofold long-memory behaviour of the return series in the conditional mean (Eq. (1)) and volatility (variance, Eq. (3)) are respectively captured by the d_m and d_v parameters. Recall that $\nu_t = \epsilon_t^2 - h_t$ is the innovation and L is the lag operator. Bring in mind that $0 < d_m < 1$ and $0 < d_v < 1$. In this regard, for both d_m and d_v, a value equal to zero indicates presence of short memory, a value less than 0.5 indicates presence long memory, and a value larger than 0.5 indicates that the series are nonstationary.

Finally, the quasi-maximum likelihood estimation method is employed to estimate all parameters of the mean and variance equations. The loglikelihood function is expressed as follows:

$$LogLikelihood(\varepsilon_t,\theta)=\frac{-1}{2}log(2\pi)-\frac{1}{2}\sum_{t=1}^{T}\left(log(h_t)+\frac{\varepsilon_t^2}{h_t}\right) \tag{4}$$

where the errors ϵ_t^2 are assumed to follow an asymmetric normal distribution.

3. Data and results

The data is downloaded from Yahoo Finance and the period of study is split into two subperiods: September 2019 to December 2019 (123 observations) corresponding to pre-pandemic

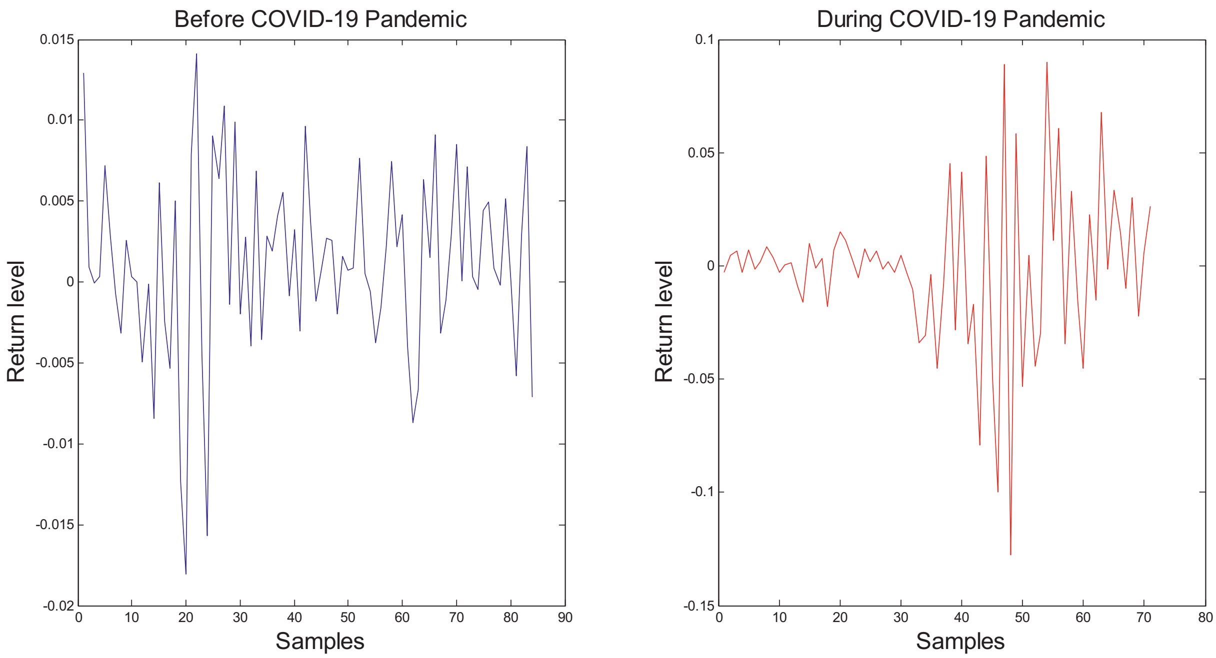

Fig. 2. Returns of S&P500 prior and throughout COVID-19 pandemic.

and January 2020 to April 2020 (120 observations) corresponding to COVID-19 pandemic. The database is composed of contains 45 cryptocurrency markets and 16 international equity markets. In one hand, the set of cryptocurrencies comprises Bitcoin, Ethereum, XRP, Tether, Bitcoin Cash, Litecoin, Binance, EOS, Stellar, Cardano, Chainlink, Monero, Tron, Ethereum, Dash, Neo, IOTA, Zcash, NEM, Dogecoin, BigiByte, Basic Attention Token, VeChain, 0X, Decred, Bitcoin Gold, Qtum, ICON, Lisk, Augur, Kyber Network, Waves, OmiseGO, Status, Siacoin, MCO, MonaCoin, Nano, DigixDAO, Komodo, Steem, Verge, BitShares, Bytecoin, Horizen, MaidSafeCoin. On the other hand, the set of international stock markets comprises TSX (Canada), S&P500 (USA), DAX (Germany), CAC40 (France), BEL20 (Belgium), MOEX (Russia), Nikkei225 (Japan), HANG SENG (China), SSE Composite (Shanghai), All Ordinaries (Australia), BSE SENSEX (Bombay, India), KOSPI (South Korea), TSEC (Taiwan), IBOVESPA (Brazil), IPC (Mexico), and MERVAL (Argentina). All our analyses are applied to returns (r_t) where $r_t = \log(p_t) - \log(p_{t-1})$. Here, p is the price level and t is time script.

To illustrate the behaviour of Bitcoin and S&P500, Figs. 1 and 2 exhibits their respective returns in the pre-pandemic period and during the pandemic period. As shown, for both of Bitcoin and S&P500, return time series followed different behaviour during COVID-19 pandemic as opposed to the period before COVID-19. Similarly, for both Bitcoin (Fig. 3) and S&P500 (Fig. 4), volatility in return time series followed different behaviour during COVID-19 pandemic in comparison with time period before COVID-19.

Besides, the boxplots of parameter d estimated from returns of cryptocurrency markets prior and throughout COVID-19 pandemic period are exhibited in Fig. 5. Similarly, those of stock markets are displayed in Fig. 6.

Also, Figs. 7 and 8 respectively exhibit the boxplots of parameter d estimated from volatilities of cryptocurrency markets and from volatilities of international equity markets before and throughout COVID-19 pandemic period. As shown in Fig. 5 to Fig. 8, the parameter d distributions have been altered during the COVID-19 pandemic.

To check if the distributions of the long memory parameter d in each type of markets are significantly affected by COVID-19 pandemic, Student's t-test (test for equality of means) and F-test (test for equality of variances) are performed. The former is used to test equality of means and the latter is employed to test equality of variances. Table 1 and Table 2 display results from t-test and F-test respectively.

Table 1
Results of t-tests applied to estimated d from return series.

Null hypothesis	p-value
Cryptocurrency markets	
Average HE before pandemic = Average HE during pandemic	0.0098
Average HE before pandemic > Average HE during pandemic	0.9951
Average HE before pandemic < Average HE during pandemic	0.0049
Stock markets	
Average HE before pandemic = Average HE during pandemic	3.3838×10^{-5}
Average HE before pandemic > Average HE during pandemic	1.0000
Average HE before pandemic < Average HE during pandemic	1.6919×10^{-5}

According to Table 1, the average HE before COVID-19 pandemic in return series of cryptocurrency markets is larger than that during the pandemic. Similarly, the average value of parameter d before COVID-19 pandemic in return series of international stock markets is larger than that during the pandemic. Therefore, the level of persistence in return series of both markets has increased throughout the COVID-19 period. Along with Table 2, the variance of parameter d before COVID-19 period in returns of cryptocurrency markets is lower than that during the pandemic. Besides, the variance of parameter d before COVID-19 period in returns of international stock markets is lower than that during the pandemic as indicated by large value of p-value (0.8340). Therefore, during COVID-19 pandemic, the level of variability in persistence in return series has increased in both categories of markets.

Finally, t-test is performed to check if the distributions of the long memory parameter d are dissimilar between cryptocurrency and international stock markets before and throughout the pandemic. The findings are presented in Table 3 and in Table 4. According to Table 3, prior to pandemic, the average value of parameter d in return series of cryptocurrency markets is statistically equal to that of return series of stock markets as computed p-value is the highest (0.9667). Similarly, throughout COVID-19 pandemic,

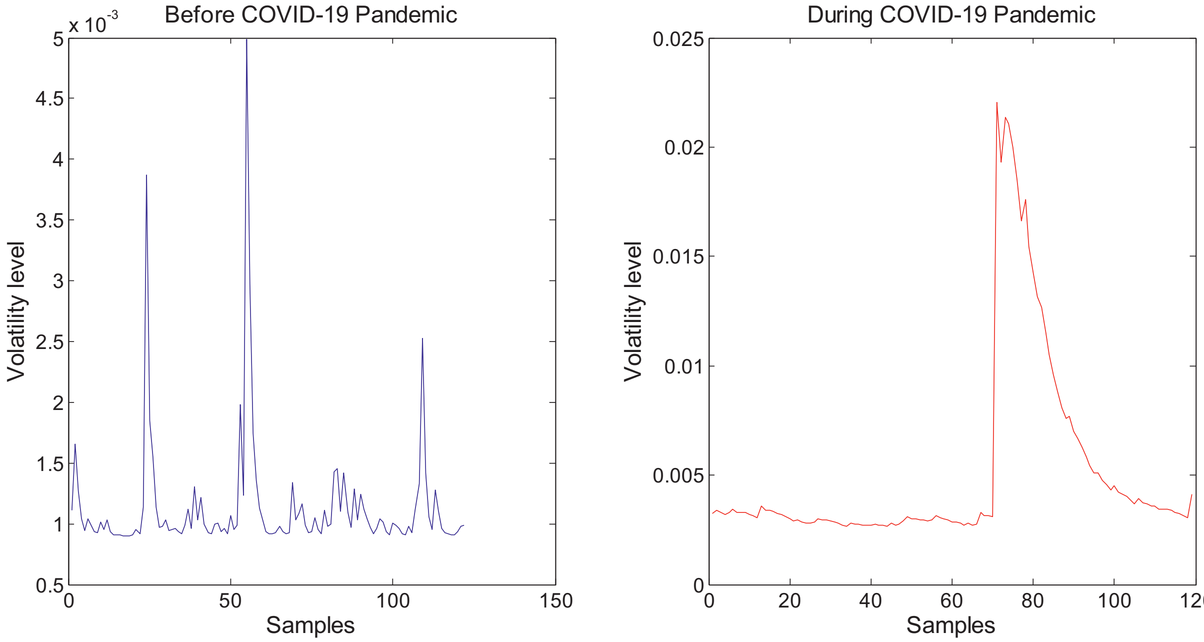

Fig. 3. Bitcoin volatility prior and throughout COVID-19 pandemic.

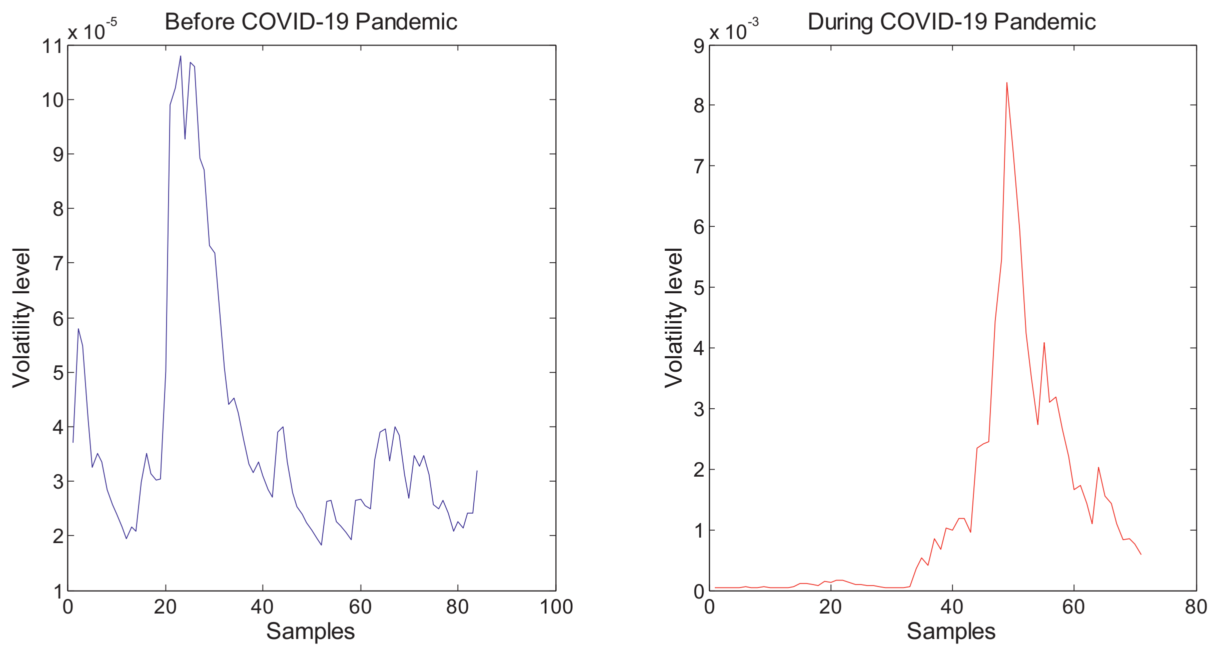

Fig. 4. S&P500 volatility prior and throughout COVID-19 pandemic.

Table 2
Results of *F*-tests applied to estimated *d* from volatility series.

Null hypothesis	*p*-value
Cryptocurrency markets	
Variance of HE before pandemic = Variance of HE during pandemic	1.5249×10^{-5}
Variance of HE before pandemic > Variance of HE during pandemic	7.6246×10^{-6}
Variance of HE before pandemic < Variance of HE during pandemic	1.0000
Stock markets	
Variance of HE before pandemic = Variance of HE during pandemic	0.3319
Variance of HE before pandemic > Variance of HE during pandemic	0.1660
Variance of HE before pandemic < Variance of HE during pandemic	0.8340

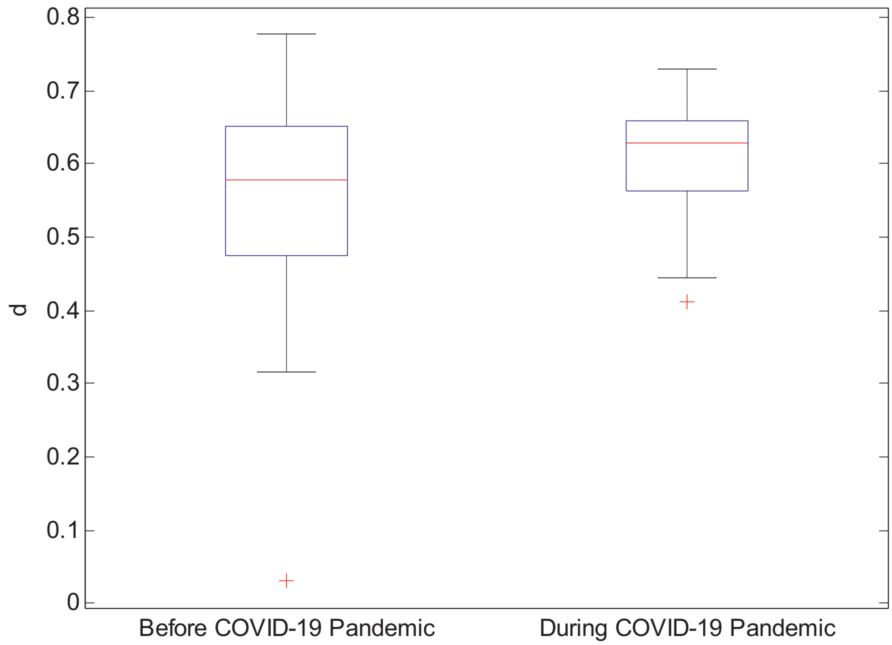

Fig. 5. Boxplots of parameter d (Eq. (1)) estimated from returns of cryptocurrency markets prior and throughout COVID-19 pandemic.

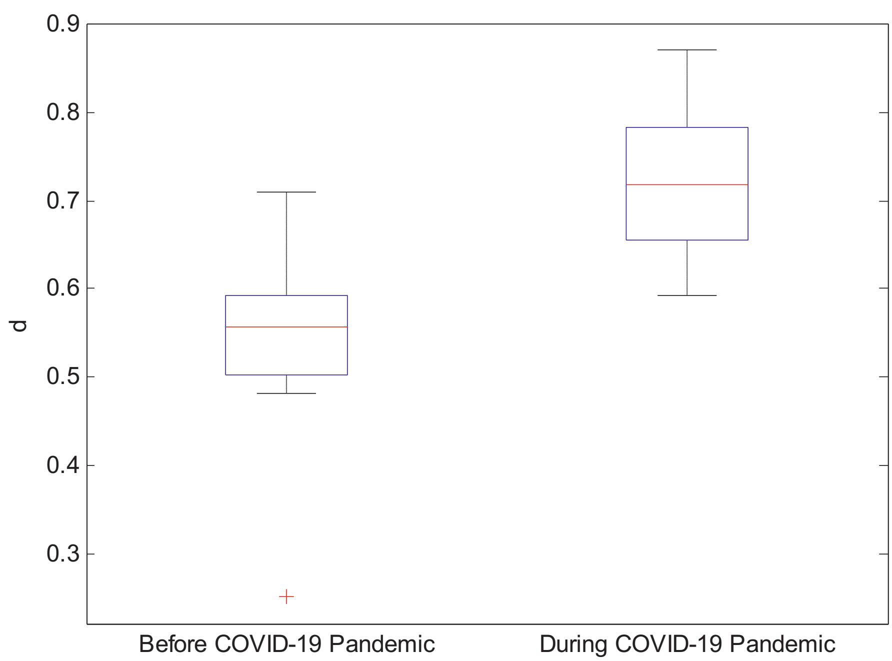

Fig. 6. Boxplots of parameter d (Eq. (1)) estimated from returns of international markets prior and throughout COVID-19 pandemic.

Table 3
Results of t-tests applied to compare long memory in return series.

Null hypothesis	p-value
Before COVID-19 pandemic	
Average HE in cryptocurrency markets = Average HE in stock markets	0.9667
Average HE in cryptocurrency markets > Average HE in stock markets	0.4833
Average HE in cryptocurrency markets < Average HE in stock markets	0.5167
During COVID-19 pandemic	
Average HE in cryptocurrency markets = Average HE in stock markets	1.0000
Average HE in cryptocurrency markets > Average HE in stock markets	0.5000
Average HE in cryptocurrency markets < Average HE in stock markets	0.5000

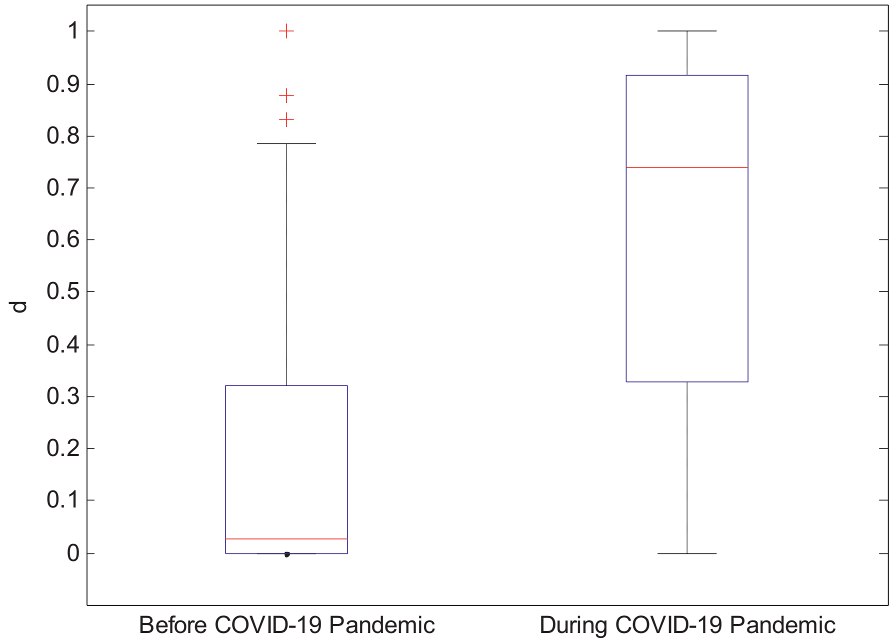

Fig. 7. Boxplots of parameter *d* (Eq. 8) estimated from volatilities of cryptocurrency markets prior and throughout COVID-19 pandemic.

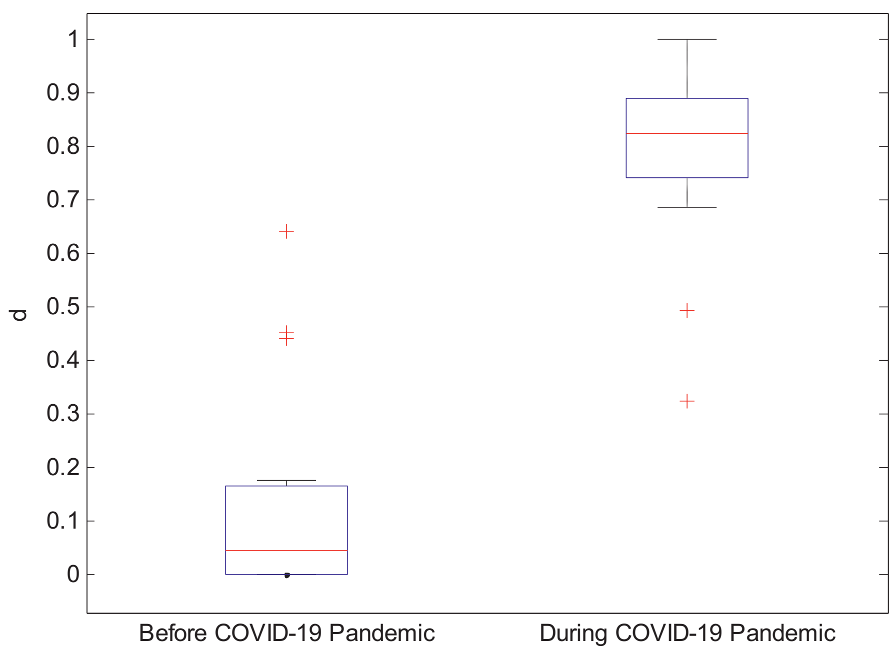

Fig. 8. Boxplots of parameter *d* (Eq. 8) estimated from volatilities of international stock markets prior and throughout COVID-19 pandemic.

Table 4
Results of *t*-tests applied to compare long memory in volatility series.

Null hypothesis	*p*-value
Before COVID-19 pandemic	
Average HE in cryptocurrency markets = Average HE in stock markets	0.3089
Average HE in cryptocurrency markets > Average HE in stock markets	0.1545
Average HE in cryptocurrency markets < Average HE in stock markets	0.8455
During COVID-19 pandemic	
Average HE in cryptocurrency markets = Average HE in stock markets	0.0772
Average HE in cryptocurrency markets > Average HE in stock markets	0.9614
Average HE in cryptocurrency markets < Average HE in stock markets	0.0386

parameter *d* average value in return series of cryptocurrency markets is statistically equal to that of return series of stock markets as calculated *p*-value is the highest (1.000). Therefore, return series in both markets exhibited comparable degree of persistence prior and throughout the COVID-19 pandemic. Consistent with Table 4, before COVID-19 pandemic, average value of parameter *d* in volatility series of cryptocurrency markets is statistically lower than that of volatility series of stock markets as the *p*-value is the highest (0.8455). Thus, volatility series in cryptocurrency exhibited low degree of persistence compared to international stock markets prior to pandemic period. In contrary, during the COVID-19 period, the average value of parameter *d* in volatility series of cryptocurrency markets is statistically larger than that of volatility series of stock markets as the *p*-value is the highest (0.9614). As a result, volatility series in cryptocurrency exhibited high degree of persistence compared to international stock markets during the COVID-19 period.

4. Conclusion

The COVID-19 pandemic greatly impacted world economy. To measure the its effect on long memory in returns and volatility of cryptocurrency and international stock markets, our paper uses ARFIMA and FIGARCH models as they are effective in estimating long memory parameter while accounting for volatility clustering and asymmetry in returns and volatilities. So far, modelling properties of return and volatility in cryptocurrencies and stocks is crucial in quantitative finance literature since return forecast is determinant for asset valuation and allocation; and, volatility forecast is an important input for hedging strategies, and risk management.

The empirical results showed that (*i*) the level of persistence in return series of both markets has increased throughout the COVID-19 pandemic, (*ii*) throughout COVID-19 pandemic, level of variability in persistence in return series has increased in both categories of markets, (*iii*) return series in both categories of markets exhibited comparable degree of persistence prior and during the COVID-19 pandemic, and (*iv*) volatility series in digital currencies exhibited high degree of persistence as opposed to international equity markets during the pandemic. As a result, it is concluded that COVID-19 pandemic has significantly altered long memory in returns and volatility series of cryptocurrency and international stock markets. Although the COVID-19 pandemic is not over yet, the obtained results are really important to consider for better investment strategies under the current situation. For future work, we will consider a larger sample when the COVID-19 is hopefully over and we will examine a large set of commodity markets.

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.

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