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Bitcoin as a Safe Haven during COVID-19 Disease

Luisanna Cocco *, Roberto Tonelli and Michele Marchesi

Department of Mathematics and Computer Science, University of Cagliari, 09123 Cagliari, Italy; roberto.tonelli@unica.it (R.T.); marchesi@unica.it (M.M.)
* Correspondence: cocco@unica.it

Abstract: In this paper, we investigate the role of Bitcoin as a safe haven against the stock market losses during the spread of COVID-19. The performed analysis was based on a regression model with dummy variables defined around some crucial dates of the pandemic and on the dynamic conditional correlations. To try to model the real dynamics of the markets, we studied the safe-haven properties of Bitcoin against thirteen of the major stock market indexes losses using daily data spanning from 1 July 2019 until 20 February 2021. A similar analysis was also performed for Ether. Results show that this pandemic impacts on the Bitcoin status as safe haven, but we are still far from being able to define Bitcoin as a safe haven.

Keywords: safe haven; bitcoin; ether; regression model; COVID-19; economic crisis

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1. Introduction

On 31 December 2019, the Municipal Health Commission of Wuhan (China) reported pneumonia cases of unknown origin in the city of Wuhan to the World Health Organization. On 9 January 2020, the Chinese Center for Disease Control and Prevention (China CDC) reported to have identified SARS-CoV-2 as the agent that causes the respiratory disease and spreads the genomic sequence to realize diagnostic testing. This new typology of coronavirus was later called COVID-19. On 30 January 2020, the World Health Organization (WHO) declared the Coronavirus epidemic in China as International emergency of public health, and on 28 February 2020, this organization declared the threat level for this coronavirus epidemic as very high. On 11 March 2020, WHO declared the spread of COVID-19 a pandemic spread all over the planet.

In the past, other types of coronavirus have spread worldwide. Think of the severe acute respiratory syndrome (Sars), that spread worldwide in 2002 and 2003 or the Middle East respiratory syndrome (MERS) present since 2012. However, COVID-19 clearly differs from these. Most of the Sars- and Mers-infected people were/are seriously ill. With COVID-19, however, the infected people can have a slight infection or even show no symptoms. For this reason, controlling the spread of COVID-19 is much more difficult than controlling that of Sars or Mers.

According to the World Health Organization, the number of confirmed cases worldwide is 47,596,856 and the number of confirmed deaths is 2,462,911, (data updated on 22 February 2021 https://www.who.int/emergencies/diseases/novel-coronavirus-2019).

COVID-19 has blocked the global economy. The discontinuity of Chinese imports has heavily impacted the export economy of countries around the world. Many sectors of activity are/were in crisis due to the quarantine of workers, the decrease in reserves and the insufficient cash flows. There has been a collapse in crude oil prices of around 30%, a massive drop in the US indexes of over 6% and for the first time in history, the entire US treasury has fallen by below 1%.

COVID-19 has had negative impacts on all sectors of financial activity, including the sector of cryptocurrencies. Indeed, mining companies have suffered from both the discontinuity of Chinese imports, as many mining equipment suppliers are based in China, and both from bitcoin price drops in March. Many of the major mining platforms block their activity when the bitcoin price reaches set limit values, and resume their activity when the price of Bitcoin goes up. The blocking of the activity of these platforms has a significant impact on the Bitcoin hashrate, which touched its lowest rates, 94.158 EH/s on 22 March 2020, and 90.293 EH/s on 26 May 2020 (ref. https://www.blockchain.com/charts/hash-rate). Bitcoin's price has fluctuated widely from around USD 10,000 on February 2020 to USD 4830 on 13 March 2020, to USD 15,071 on 5 November 2020, and is now around USD 48,142.95 on 22 February 2021 at the time of writing (ref. https://www.blockchain.com/charts/market-price).

The collapse in crude oil prices, with the breakdown between Russia and OPEC, and the spread of coronavirus—soon declared a pandemic—triggered the biggest decline in the stock market since the global financial crisis of 2009 and have forced society to reorganize at all levels.

In recent months, many have wondered to what extent the pandemic will impact the financial market and the life of people in general. In the last few months, several research papers have appeared in literature to investigate the impact of COVID-19 on the world economy ([1–5]), and in order to investigate which instruments in this period are the best candidates as safe havens.

Our work can be located within the literature strand that is about understanding and analyzing bitcoin's status as a safe haven or hedge. A hedge is defined as an uncorrelated or negatively correlated asset with another asset or portfolio on average. Contrarily, an asset is defined as a safe haven when these properties apply not on average but in times of market stress or turmoil.

In this work, we further investigate the role of Bitcoin as a safe haven, as a useful investment to protect from the downward movements of the financial market during the spread of COVID-19. By performing a regression analysis, as was carried out in [6–8], and an analysis of the dynamic conditional correlations (DCCS) among indexes, as carried out in [8,9], we studied the safe- haven properties of Bitcoin on major stock market indexes, oil, gold, the general commodity index and the US dollar index from 1 July 2019 to 20 February 2021. Specifically, we studied the safe-haven properties of Bitcoin against thirteen of the major stock market indexes losses to tried to model the real dynamics of the markets in the best possible way. A similar analysis was also performed for Ether.

Following the trend of the recent papers appearing in the literature, our paper presents an analysis of the status of Bitcoin/Ether as a safe haven during COVID-19 disease, attempting to accurately describe the relations among these two cryptocurrencies and the entire world economy modeled through 13 financial market indexes.

Differently from the work by Mariana, we analyzed a market represented by fifteen indexes (if we also count Bitcoin and Ether) and a larger time interval, since in the work just quoted the authors considered five indexes and a time interval ranging between 1 July 2019 and 6 April 2020.

A representation of the market similar to ours was made by Bouri et al. [9] which conducted a study considering the same indexes but by using a regression model based on dynamic conditional correlation, applied to a dataset spanning from July 2011 to December 2015.

In this paper, we present a regression analysis using as regressors, in addition to the index returns, the forex (FX) volatility and dummy variables defined around crucial dates/intervals during the COVID-19 pandemic. Note that as described next, the FX volatility refers to the volatility in the FX market, that is in the foreign exchange market, more commonly known as the currency market, that is a market in which one currency is exchanged for another. The crucial dates/intervals during the COVID-19 pandemic vary among 7, 10 and 14 days starting from a specific date. We individuated five dates, hence fifteen intervals, denoted in the following as *event windows*. within which crucial events linked to the COVID-19 spread can be individuated (ref. https://www.thinkglobalhealth.org/article/updated-timeline-coronavirus (accessed on 22 February 2022)). The five individuated dates are the following:

- 5 March 2020: Outbreaks increase in Europe and the Americas, and there are more and more deaths outside China.
- 16 August 2020: The COVID-19 cases in Europe reach the March levels.
- 20 October 2020: France reports a new daily record and Italy imposes the harshest lockdown since March.
- 12 November 2020: Pfizer-BioNTech announces 94% vaccine efficacy and Moderna announces 94% vaccine efficacy.
- 14 January 2021: The global death toll passes 2 million and the cases of new virus strains increase.

Let us conclude this introduction by underlining that contrary to previous studies, our work performs three different analysis to support the final considerations on the status of Bitcoin and Ether as safe havens during the pandemic. We conducted two regression analyses to study the safe-haven properties of Bitcoin against losses of the major stock market indexes, oil, gold, general commodity index and the US dollar index. We performed a regression analysis using dummy variables defined around the COVID-19 pandemic events, and another regression analysis using dummy variables for extreme values of all index returns and the forex volatility, neglecting the dummy variable for COVID-19 (see Section 3.2.1 for more details). Additionally, we performed a dynamic conditional correlation analysis based on the DCC-Garch model to support the results of the previous analysis and give more robust results. In addition, this paper studies a market constituted by fifteen stock indexes to simulate a more realistic market. Considering such a market allows us to shed light on the interrelation among cryptocurrencies and stock indexes, all significant for a complete analysis of the market both in regular market conditions or in time of stress, to investigate the Bitcoin's and Ether's safe-haven properties that allow investors to protect their portfolios during market turmoil, such as during the COVID-19 pandemic.

The paper is organized as follows. Section 2 illustrates the related work. Section 3 describes the used historical series, the regression and DCC models, and the obtained results. Finally, Section 4 concludes the paper.

2. Related Work

As always happens during market uncertainty, the appeal of investments in instruments that should increase their value are increasingly attractive. Safe havens include commodities, U.S. Treasuries, legal currencies, hedge funds, precious metals such as gold and silver, real estate and even art. Recently cryptocurrencies have been added to this list, and several works on this topic appeared.

Let us cite some works. Baur et al. [6] presented a regression analysis of Bitcoin returns on S&P500 returns and interaction terms with dummies for extreme values of S&P500 and FX volatility returns. The model used is similar to the one by Ranaldo et al. [7] and highlights that Bitcoin does not act as a safe haven or hedge both using explicit crisis event date interactions and using dummies for extreme values of S&P500 and FX volatility returns. Dyhrberg [10] explored the hedging capabilities of bitcoin by using the GARCH methodology and his analysis results show that bitcoin can be used as a hedge against stocks in the Financial Times Stock Exchange Index, and in the short-term, against the American dollar. Bouri et al. [9] used a dynamic conditional correlation model to examine whether Bitcoin can act as a hedge and safe haven for major world stock indexes, bonds, oil, gold, the general commodity index and the US dollar index. Their results showed that the hedging and safe-haven properties of Bitcoin vary between horizons. Bitcoin can be used for diversification only, can act as a strong safe haven against weekly extreme downward movements in Asian stocks and is a poor hedge. Stensås et al. [11] investigated whether Bitcoin acts as a diversifier, hedge, or safe haven. By using a GARCH Dynamic Conditional Correlation (DCC) model, they showed that Bitcoin acted as a hedge in most of the developing countries, as a diversifier in developed countries, and as a safe-haven asset for both the US and non-US investors during the US election in 2016, the Brexit referendum in 2016, and the burst of the Chinese market bubble in 2015. Baur et al. [12] analyzed whether stablecoins can provide characteristics of safe haven against Bitcoin, and found that stablecoins can be considered a safe haven when the Bitcoin price changes acquire extreme negative values. Kliber et al. [13] analyzed the properties of Bitcoin as a hedge, diversifier or safe haven on various stock markets, considering five countries characterized by very different economic situations (Japan, Venezuela, China, Estonia, and Sweden). They applied the Stochastic Volatility Model with the Dynamic Conditional Correlation and concluded that the Bitcoin properties vary depending on the trade taken into account, which can be on the local bitcoin exchanges or in the global one. Selmi et al. [14] studied the same properties but against extreme oil price movements by using a quantile-on-quantile regression model. They found that these properties are sensitive to the market conditions of these two assets, that can bear, normal or bull, and to the oil price movements, that can be in a downside, normal or upside regime, and that during times of political and economic turmoil, Bitcoin and gold can protect the investors' cash. Contrary to the current literature on these properties of cryptocurrency, Wang et al. [15] analyzed a much wider market that includes 973 forms of cryptocurrency and 30 international indexes from a dynamic perspective. Paule-Vianez et al. [16] studied the influence of Economic Policy Uncertainty (EPU) on Bitcoin returns and volatility to determine whether Bitcoin behaves as a safe-haven asset. An increase in EPU implies for safe havens, such as gold, an increase in their returns and volatility, while for conventional speculative assets an increase in EPU implies an increase in their volatility and a reduction in their returns. By using simple linear regression and quantile regression models, they found that Bitcoin shows characteristics of safe havens during more uncertain times, just like gold. Additionally, Shahzad et al. [17] addressed the question of the Bitcoin safe-haven property during extreme market conditions. They used a bivariate cross-quantilogram approach, revealing that the safe haven roles of Bitcoin, gold, and commodities vary with time and differ depending on the stock market indexes taken into account. Smales [18] studied the safe haven property of Bitcoin considering that Bitcoin is more volatile, less liquid and costlier to transact than other assets, contrary to current literature that studied this property by Bitcoin correlation with other assets during times of market stress. Aysan et al. [19] investigated the future possibility of a digital renminbi in place of the US dollar in international commerce.

Finally, let us cite the work by Urquhart et al. [20], that studied the relationship between Bitcoin and several currencies at hourly frequencies. They found that Bitcoin acts as an intraday hedge for CHF, EUR and GBP, as a diversifier for AUD, CAD and JPY, and as safe haven for CAD, CHF and GBP during periods of market turmoil.

During the spread of COVID-19, Bitcoin as a safe-haven asset has been subject of numerous research works again ([5,8,21–24]). Cheema et al. [21] examined the role of the safe havens both from stock market and cryptocurrency losses during the COVID-19 pandemic by using a generalized auto-regressive conditional heteroskedasticity (GARCH) model. Their results showed that gold has lost its safe haven status; that S&P U.S. Treasury bill index, S&P U.S. Treasury bond index, and the U.S. Dollar index act as strong, safe havens from the stock market losses and as a weak safe haven from BTC losses; and that Tether (a dollar-backed stable coin) is a weak safe haven against stock market and BTC losses. Corbet et al. [23] analyzed the relationships between the largest cryptocurrencies and the polarity and subjectivity of social media data based on the development of COVID-19. They found significant growth in both returns and volume traded in the large cryptocurrencies, demonstrating that these cryptocurrencies act as a store of value during the COVID-19 period. Conlon et al. [24] investigated the safe-haven properties of Bitcoin during the COVID-19 bear market. Computing Value at Risk (VaR) and conditional value at risk (CVaR) by using Cornish–Fisher expansion, they found that Bitcoin is not a safe haven and allocation to Bitcoin increases portfolio downside risk. Rubbany et al. [25], by using the wavelet coherence framework, showed that, with a proxy of market stress cryptocurrencies behave as safe-haven assets and with a proxy of market turbulence, cryptocurrencies behave like traditional assets. Ji et al. [26] re-evaluated the safe-haven role of gold, cryptocurrency, foreign exchange and commodities monitoring the changes in the left quantiles of asset returns, and assessing whether the introduction of a safe-haven asset can offset a tail change in the equity index. In addition, the authors performed a cross-quantilogram analysis comparing the directional predictability of the pair-wise asset returns on left-quantiles in both normal market conditions and the COVID-19 period, and showed that most of the assets taken into account has weak properties of safe haven becomes, contrary to gold and soybean commodity futures that have robust safe-haven properties during the COVD-19 pandemic. Baur et al. [27] proposed a safe haven index and identified some stylized facts for safe-haven assets. In addition, they revealed that the COVID-19 shock in March 2020 made the safe haven index fall with respect to previous crises. Bedowska et al. [28] investigated the safe-haven properties of gold and Bitcoin and Ether. They found that only gold can be a strong safe haven against the stock market indexes, but not during the COVID-19 pandemic, while Bitcoin and Ether only occasionally act as weak safe-havens, specifically Ether against DAX or S&P500, and Bitcoin against FTSE250, STOXX600 and S&P500. Dutta et al. [29] investigated the safe-haven properties of gold and Bitcoin for the international crude oil markets during the COVID-19 pandemic, using time-varying correlations, hence by a DCC-GARCH model. Results suggested that gold is a safe-haven asset, Bitcoin is only a diversifier for crude oil, and that the portfolio risk is minimized by including oil and gold in the portfolio rather than oil and Bitcoin. Abdelsalam et al. [30] investigated the effects of COVID-19 in the US tourism subsectors.

Understanding which could be the protections/the investments to perform against market turmoil and downward movements is a crucial aspect during financial or natural disasters such as the COVID-19, a pandemic that has been impacting the whole of society and all sectors of the world economy. During the onset of COVID-19, Bitcoin price fell alongside stock indexes, but contrary to stock indexes it has recovered its value, going up to USD 48,000 in February 2021, and positioning itself as a reasonable investment.

3. Data and Methods

The data investigated in our analysis were downloaded from https://finance.yahoo.com/ and https://www.nasdaq.com/ web sites and ranged between 1 July 2019 (as in [8]) and 20 February 2021. The data include price index values for Bitcoin, Ether and financial assets referring to the largest economies in the world. For Germany, we downloaded the Global X DAX Germany ETF (the variable DAX refers to this index); for Japan we downloaded the SSE A Share Index (denoted in our work by the SS variable); for China the Nikkei 225 index ($N225$); for the US the S&P 500 index ($GSPC$); and for the UK the FTSE 100 index ($FTSE$). In addition we also considered three benchmarks from Morgan Stanley Capital International (MSCI) indexes, specifically the MSCI World Index Futures—ICUS, denoted by $URTH$ variable, the iShares MSCI Europe Financials ETF ($EUFN$) and the iShares Trust—iShares Core MSCI Pacific ETF ($IPAC$) and the U.S. Dollar index (DX). Finally, we downloaded an index referring to commodity: the S&P GSCI Index (GD), the VANGUARD BD IDX FD (BND), the Brent Crude Oil Last Day Finance index (BZ), the Gold Aug 20 (GC), the Bitcoin prices (BTC) and the Ether price (ETH).

Figures 1 and 2 show the time trend of the financial market index's value and of the Bitcoins and Ether's value.

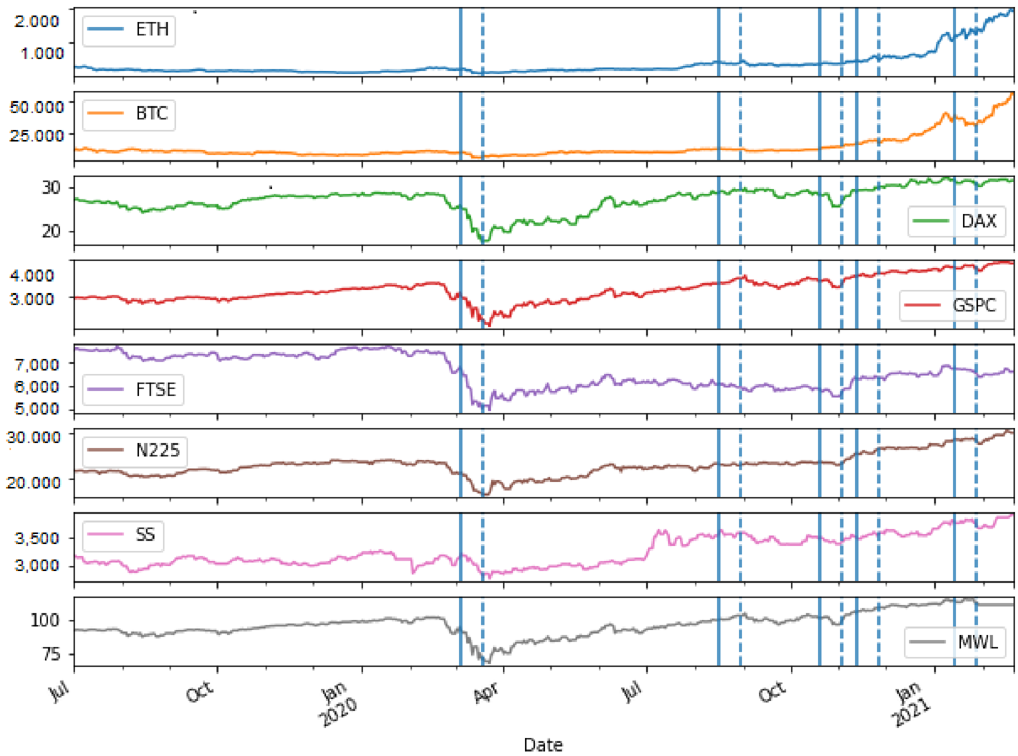

Figure 1. Value of some financial market indexes and of the Bitcoin and Ether (vertical solid lines refer to the individuated dates, and the vertical dashed lines refer to these dates plus 14 days).

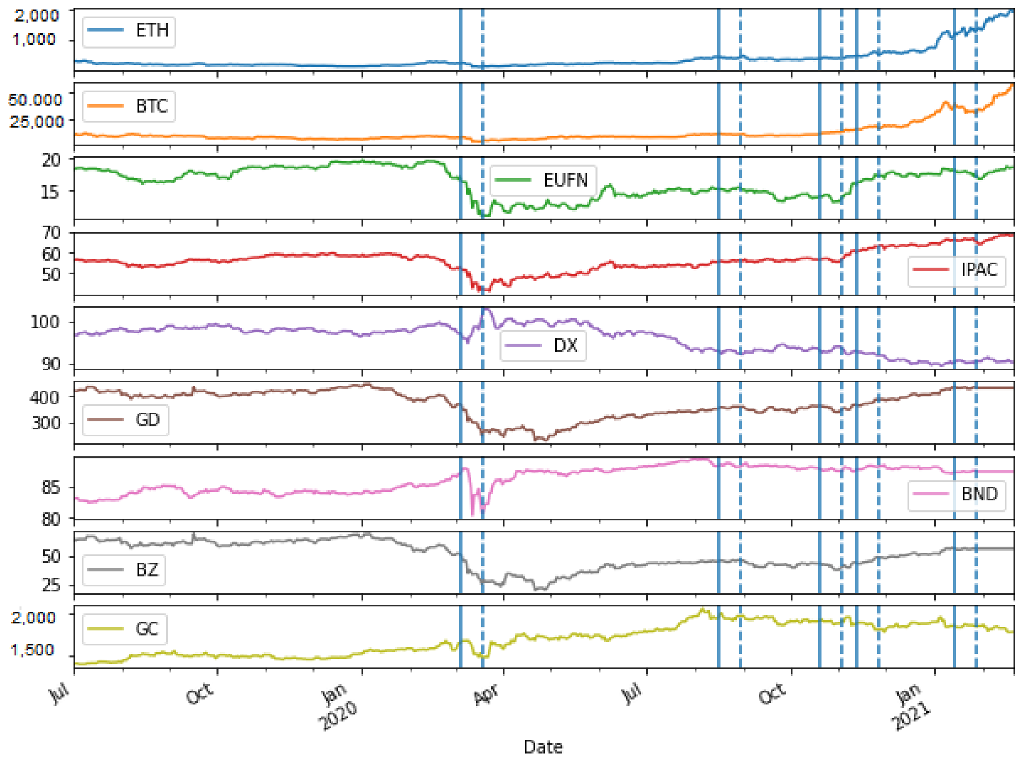

Figure 2. Value of the remaining financial market indexes and of the Bitcoin and Ether.

All indexes were down in the first quarter of 2020, due to the COVID-19 pandemic and to the consequent global economic turmoil, but only Bitcoin went up incredibly in the last few months after the fall.

Tables 1 and 2 show some statistics of the index returns. Specifically some measures of central tendency, which describe the center of the data, the mean and median, the most popular measures of dispersion as the standard deviation, the variance, the interquartile range, the skewness, which is the measure of the symmetry for the returns about their mean, and the kurtosis, which is a measure of the tailedness, hence of the probability distribution shape of the returns, are illustrated. The tables show that the cryptocurrency returns have a higher maximum value, and a lower minimum value, than those of the stock index returns. The kurtosis values are positive for all indexes and those for the BTC and ETH returns are higher than those of the stock indexes but that of the BND returns. The skewness values are negative for almost all the returns but that of the DX and $N225$ returns.

Table 1. Return statistics.

	retBTC	**retETH**	**retDAX**	**retGSPC**	**retFTSE**	**retN225**	**retSS**	**retMWL**
mean	0.002705	0.003129	0.000265	0.000450	−0.000221	0.000543	0.000347	0.000317
std	0.039739	0.050453	0.015741	0.014854	0.012917	0.011302	0.009361	0.014131
min	−0.464730	−0.550732	−0.120154	−0.127652	−0.115117	−0.062736	−0.080343	−0.120786
25%	−0.013128	−0.017409	−0.001918	−0.001468	−0.003025	−0.002149	−0.001755	−0.000990
50%	0.001331	0.001802	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.017542	0.026513	0.005442	0.004696	0.003396	0.003434	0.003135	0.004058
max	0.171821	0.230695	0.092150	0.089683	0.086664	0.077314	0.055535	0.087061
kurtosis	33.512346	25.807796	15.162256	20.116052	17.408403	10.062584	13.570148	23.031934
skewness	−2.479123	−2.264091	−1.426191	−1.188401	−1.338449	0.281258	−1.123514	−1.690548

Table 2. Return statistics.

	retEUFN	**retIPAC**	**retDX**	**retGD**	**retBND**	**retBZ**	**retGC**
mean	0.000009	0.000319	−0.000124	0.000031	0.000092	−0.000234	0.000404
std	0.019565	0.012227	0.003238	0.015295	0.003994	0.031627	0.009929
min	−0.162119	−0.111030	−0.016262	−0.127625	−0.055920	−0.279761	−0.051069
25 %	−0.003926	−0.001580	−0.001323	−0.001786	−0.000343	−0.004974	−0.001366
50%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.004352	0.003943	0.000953	0.003769	0.000953	0.006553	0.004037
max	0.113003	0.072607	0.015786	0.073011	0.041335	0.190774	0.057775
kurtosis	20.573739	22.246038	5.062571	21.876907	89.795265	25.313214	8.024764
skewness	−1.757299	−1.690733	0.432049	−2.033562	−3.179314	−1.577847	−0.249648

3.1. Regression and DCC Model

Following the regression models proposed by Ranaldo and Söderlind [7] and Baur et al. [6], we defined a multiple regression model with a dummy variable, called "Covid", equal to 1 in the *event windows* described in the previous sections. The model is the following:

$$\begin{aligned} retCrypto(t) = a_0 + (b_0 + b_1 Covid) * Vol(t) + \\ \sum_i [(c_{0,i} + c_{1,i} Covid) * retIndex_i(t)] + \\ d_0 retCrypto(t-1) + e_0 Vol(t-1) + \sum_i [f_{0,i} retIndex_i(t-1)] + \epsilon(t) \end{aligned} \quad (1)$$

where

- *retCrypto* represents the daily Bitcoin/Ether returns;
- *Vol* represents the volatility in the FX market. It is the average daily volatility across the three currency pair *EUR-USD*, *JPY-USD*, *GBP-USD* as in work [6], (Let us underline

that as a measure of volatility for each currency pair we computed the logarithmic returns and then we applied the moving standard deviation calculated using the rolling method of a pandas DataFrame with a window equal to five days as in [23]);

- r_i represents the returns of the i-th index, with i varying from 1 to 13, that is the number of indexes downloaded from the Yahoo finance website as already described ($i = 1$ for $retGSPC$, $i = 2$ for $retDAX$, $i = 3$ for $retFTSE$, $i = 4$ for $retN225$, $i = 5$ for $retSS$, $i = 6$ for $retURTH$, $i = 7$ for $retEUFN$, $i = 8$ for $retIPAC$, $i = 9$ for $retDX$, $i = 10$ for $retGD$, $i = 11$ for $retBND$, $i = 12$ for $retBZ$, and $i = 13$ for $retGC$).
- *Covid* is an indicator variable for days in the sample that correspond to the days within the *event window*.

This is a multiple regression model in which Bitcoin/Ether returns ($retBTC(t)/retETH$) represent our dependent variable. Instead, the returns of the above-described indexes ($retIndex_i(t)$), along with some interaction terms, represent our independent variables. Interaction terms are defined as the product among different independent variables, precisely as the product between the dummy variable and the returns of every index and between the dummy variable and FX volatility. The model includes lagged variables to account for expected values as in [7]. Note that with the introduction of the non-linear effects through the dummy variables we aim to capture properties that have value only in precise time intervals that correspond to the *event windows*. The dummy for COVID-19 was set to 1 in these *event windows*, and an analysis for the three intervals of 7, 10 and 14 days defined around each individuated date was performed in order to evaluate the robustness of the results.

As already mentioned, an asset is defined as a safe haven when it is uncorrelated or negatively correlated with another asset, not on average, but in times of market stress or turmoil. Referring to the above-described models, if the coefficients b_1 and $c_{1,i}$ are statistically significant and the first is positive, and the second ones are negative, in precise intervals, then Bitcoin/Ether acts as a safe haven against FX volatility and index returns.

We computed the p-value of each regressor to analyze its relation with the dependent variable. Note that our goal is to represent statistically conditioned action that would otherwise be impossible to describe. We are interested in the significance of each individual coefficient and not in the overall significance of the regression, and the significance of each coefficient depends on the presence or absence of any other variable in the model.

In addition to the regression analysis we solved a DCC model with the aim of computing the time-varying correlations among stock indexes. We used the generalized autoregressive conditional heteroscedasticity dynamic conditional correlation model, the well-known GARCH DCC model by Engle [31].

The DCC model is defined as follows. Let us start with the typical formulation of a multivariate historical series of returns:

$$z_t = \mu_t + a_t \tag{2}$$

where

- $\mu_t = E(z_t|F_{t-1})$ is the conditional expectation of z_t given F_{t-1}, hence it is the predictable component of z_t, hence the information available at the time $t-1$,
- a_t is the unpredictable component of z_t, represents the innovation and is equal to $a_t = \Sigma^{1/2}\epsilon_t$, where:
  - ϵ is a sequence of independent and identically distributed random vectors, such that $E(\epsilon_t) = 0$ and $Cov(I_k)$,
  - $\Sigma_t^{1/2}$ is the square-root matrix of Σ_t, that is the volatility matrix.

The DCC models divide the modeling of a stochastic process into two sets of equations. The first controls the temporal evolution of the conditioned average while the second describes the dynamic dependence of the volatility matrix. Precisely, the DCC model:

- Uses a Vector Autoregressive model VAR(p) to estimate the conditional mean $\hat{\mu}_t$ of the historical series of returns where $\hat{a}_t = z_t - \hat{\mu}_T$ are the residues;
- Applies univariate volatility models, such as the GARCH models, to each component of the series $\hat{a}_{it}$ estimating $\hat{\sigma}_{ii,t}$;
- Atandardizes the innovations through $\hat{\eta}_{it} = \frac{\hat{a}_{it}}{\sqrt{\hat{\sigma}_{ii,t}}}$ and adapts a DCC model to $\hat{\eta}_t$ (ref. https://www.dedaloinvest.com/education/didattica-investimenti/garch (accessed on 22 February 2022)).

  The DCC model proposed by Engle [31] is defined as:

$$Q_t = (1 - \Theta_1 - \Theta_2)\bar{Q} - \Theta_1 Q_{t-1} - \Theta_2 \eta_{t-1}\eta^{'}_{t-1}$$

$$\rho_t = J_t Q_t J_t$$

where

- η_t is the standardized marginal vector of innovations,
- $\eta_{it} = \sqrt{\sigma}_{ii,t}$,
- ρ_t is the volatility matrix of η_t,
- $\bar{Q}$ is the unconditional covariance matrix of η_t,
- Θ_i are non-negative real numbers.

Through the DCC model just described we can compute the dynamic conditional correlations between the pairs of indexes taken into account in our work, in order to extrapolate useful information for our research question that investigates the safe-haven properties for Bitcoin/Ether.

3.2. Results

To solve the regression model just illustrated, we used the *statsmodels* Python package, and precisely used the Heteroskedasticity and Autocorrelation Consistent (HAC) robust covariance matrix for estimating the model's coefficients, as in works [6,7] (HAC corrects for autocorrelation, but also for heteroskedasticity. Precisely in the used python package the corrected standard errors are known as HAC or Newey–West standard errors. In other words, the Newey–West estimator is an approximation of the covariance matrix, used in those real cases for which the standard hypotheses of linear regression are inapplicable. It is used to eliminate the autocorrelation of the observed data and the heteroskedasticity of the deviations of the model with respect to the real value of the reference population (for major details see http://web.vu.lt/mif/a.buteikis/wp-content/uploads/PE_Book/4-5-Multiple-collinearity.html (accessed on 22 February 2022), and http://web.vu.lt/mif/a.buteikis/wp-content/uploads/PE_Book/4-7-Multiple-heteroskedastic.html (accessed on 22 February 2022)). Newey–West standard errors with six lags are used as suggested in [32]). Note that we implemented this analysis in Python using the Jupyter Notebook, the well-known web-based interactive computational environment.

To compute the dynamic conditional correlations, hence to solve the DCC model, we used the R package called *rmgarch*.

3.2.1. Regression Model Results

The main goal of this work is investigating Bitcoin's status as a safe haven around crucial dates in the COVID-19 spread, hence around precise *event windows*.

The windows taken into account are eighteen, since for each date we considered three time intervals: one of 7 days, one of 10 days and another of 14 days, as shown in Tables 3–7, that describe the estimates of the coefficients of the regression model defined in the Equation (1). Note that only the statistically significant coefficients (the significance level is equal to 95%) are shown, while in Appendix A the complete results concerning some of the performed regression analysis are reported in tables from Tables A1–A3. The remaining results are available on request. Let us look to the results described in Tables 3 and 4, or in Table 5 that show only the variables significant to our analysis.

Table 3. Summary of regression model results about Btc taking into account the variables with significant coefficient for the first six windows taken into account.

	5 March 2020 +			16 August 2020 +		
	7 Days	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**
retIPAC	1.029	1.009	0.965	1.035	1.033	1.036
retGD	−0.41	0	−0.539	−0.561	−0.554	−0.557
retBND	0	0	0	2.211	2.198	2.197
retBZ	0.2494	0.245	0.252	0.286	0.2842	0.286
retGC	0.427	0.492	0.389	0.53	0.525	0.529
Volatility:COVID	−8.089	−5.902	−4.744	0	0	0
retGSPC:COVID	−2.769	−2.064	0	0	−18	−3.356
retDAX:COVID	−3.983	−3.82	−5.96	−1.89	−2.509	−3.719
retFTSE:COVID	4.26	4.563	0	1.29	0.85	2.619
retN225:COVID	−1.873	−2.436	0	−3.488	−3.441	−1.954
retSS:COVID	7.287	6.884	0	−1.411	−1.293	−2.162
retURTH:COVID	−2.2	−1.649	−11.179	1.859	1.129	2.703
retEUFN:COVID	4.93	3.761	6.08	3.058	2.783	2.63
retIPAC:COVID	2.799	2.69	0	−1.165	−1.873	0
retDX:COVID	2.234	1.999	9.932	1.218	1.147	0
retGD:COVID	−4.717	−4.623	0	2.09	2.602	5.564
retBND:COVID	−3.491	0	4.825	−0.485	−0.668	0
retBZ:COVID	0	0	0	0	0	−2.504
retGC:COVID	0.845	0	5.297	0	0	0
retDXprevious	0	−1.142	−1.532	0	0	0
retBNDprevious	0	0	0	−1.454	−1.466	−1.466

Table 4. Summary of regression model results about Btc considering the variables with significant coefficient for the remaining nine windows taken into account.

	20 October 2020 +			12 November 2020 +			14 January 2021 +		
	7 Days	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**
retIPAC	0.927	0.93	0.926	1.11	1.079	1.074	0.952	0.936	0.914
retGD	−0.556	−0.558	−0.551	−0.588	−0.589	−0.61	−0.584	−0.566	−0.577
retBND	2.160	2.165	2.157	2.118	2.127	2.131	2.193	2.206	2.226
retBZ	0.277	0.28	0.28	0.296	0.295	0.303	0.292	0.286	0.291
retGC	0.512	0.51	0.514	0.517	0.515	0.53	0.515	0.524	0.526
Volatility:COVID	0	0	0	−4.013	−4.28	−4.238	−5.365	−5.067	−5.021
retGSPC:COVID	1.4572	0	0	−1.939	−2.25	−6.55	−1.624	−2.993	−31.196
retDAX:COVID	0	0	0	−3.411	−3.551	−13.777	−2.227	3.798	0
retFTSE:COVID	−3.126	−3.333	0	−1.873	−2.382	3.547	0	0	0
retN225:COVID	−1.107	0	−1.932	0.643	0	−4.645	−6.326	−6.558	0
retSS:COVID	−1.786	−1.83	−1.108	1.111	1.132	−8.33	−3.885	−3.495	0
retURTH:COVID	0.688	0	0	−0.813	−0.833	6.89	0	0	0
retEUFN:COVID	0	0	0	4.299	4.092	4.674	−2.478	−5.801	0
retIPAC:COVID	1.991	2.093	3.925	−2.436	−1.558	3.2	6.443	12.388	21.231
retDX:COVID	−1.249	0	−3.135	−2.317	−2.261	−4.789	1.632	0	21.248
retGD:COVID	0.803	0	0	1.639	1.915	17.394	5.242	1.68	0
retBND:COVID	0	0	0	3.301	3.474	0	0.866	−0.613	0
retBZ:COVID	0	0	0	0.239	0.503	−7.591	4.384	0	0
retGC:COVID	0	0	0	2.58	3.458	−3.399	−4.234	−6.128	0
retDXprevious	0	0	0	0	0	0	0	0	0
retBNDprevious	−1.441	−1.436	−1.469	−1.443	−1.445	−1.421	−1.517	−1.524	−1.526

Table 5. Summary of regression model results about Btc considering only the variables with significant coefficients for our analysis.

	5 March 2020 +			**16 August 2020 +**		
	7 Days	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**
retGD	−0.41	0	−0.539	−0.561	−0.554	−0.557
retGSPC:COVID	−2.769	−2.064	0	0	−18	−3.356
retDAX:COVID	−3.983	−3.82	−5.96	−1.89	−2.509	−3.719
retN225:COVID	−1.873	−2.436	0	−3.488	−3.441	−1.954
retSS:COVID	7.287	6.884	0	−1.411	−1.293	−2.162
retURTH:COVID	−2.2	−1.649	−11.179	1.859	1.129	2.703
retIPAC:COVID	2.799	2.69	0	−1.165	−1.873	0
retGD:COVID	−4.717	−4.623	0	2.09	2.602	5.564
retBND:COVID	−3.491	0	4.825	−0.485	−0.668	0
retBNDprevious	0	0	0	−1.454	−1.466	−1.466

	20 October 2020 +			**12 November 2020 +**			**14 January 2021 +**		
	7 Days	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**
retGD	−0.556	−0.558	−0.551	−0.588	−0.589	−0.61	−0.584	−0.566	−0.577
retGSPC:COVID	1.4572	0	0	−1.939	−2.25	−6.55	−1.624	−2.993	−31.196
retDAX:COVID	0	0	0	−3.411	−3.551	−13.777	−2.227	3.798	0
retFTSE:COVID	−3.126	−3.333	0	−1.873	−2.382	3.547	0	0	0
retN225:COVID	−1.107	0	−1.932	0.643	0	−4.645	−6.326	−6.558	0
retSS:COVID	−1.786	−1.83	−1.108	1.111	1.132	−8.33	−3.885	−3.495	0
retURTH:COVID	0.688	0	0	−0.813	−0.833	6.89	0	0	0
retEUFN:COVID	0	0	0	4.299	4.092	4.674	−2.478	−5.801	0
retIPAC:COVID	1.991	2.093	3.925	−2.436	−1.558	3.2	6.443	12.388	21.231
retDX:COVID	−1.249	0	−3.135	−2.317	−2.261	−4.789	1.632	0	21.248
retGC:COVID	0	0	0	2.58	3.458	−3.399	−4.234	−6.128	0
retBNDprevious	−1.441	−1.436	−1.469	−1.443	−1.445	−1.421	−1.517	−1.524	−1.526

The coefficients for the returns of the iShares Trust—iShares Core MSCI Pacific ETF, (*retIPAC*), for those of the VANGUARD BD IDX FD, (*retBND*), and of the Brent Crude Oil Last Day Finance index (*retBZ*), and of the Gold Aug 20, *retGC* acquire positive values in all *event windows*, but for *retBND* in the *event windows* around the 5 March 2020 date. In contrast, the coefficient for the returns of the S&P GSCI Index, (*retGD*) acquires negative values in almost all *event windows*, giving some indications of Bitcoin being a safe haven against the downward movements of this index. It is equal to zero in only one window [5 March 2020 +10 days]. Additionally, the coefficient of the lagged variable *retBNDprevious* is statistically significant and negative in twelve out of fifteen *event windows*, meaning that this variable accounts for the expected values.

The other regressors, those interacting with the dummy variable *Covid*, present values that vary across the *event windows*. The coefficients of the interaction variable, *Vol:Covid* are negative in nine out of fifteen *event windows* and equal to zero in the remaining windows. So they do not contribute to associating properties of safe haven with Bitcoin in these *event windows* against the movements of the volatility in the FX market, *Vol*.

Regarding the coefficients of the other interaction terms, the results show that many of them are statistically significant and negative, hence they contribute to associating properties of safe haven with Bitcoin in precise *event windows* against their downward movements. Additionally, positive effects are highlighted for some indexes, but of course these do not give indications for safe-haven behavior.

In the windows defined after 5 March 2020, the coefficients for *retDAX:Covid* and *retURTH:Covid* are significant and negative for all three windows of 7, 10 and 14 days.

Instead, the coefficients for *retGSPC:Covid*, *retN225:Covid*, and *retGD:Covid* are significant and negative for the first two windows of 7 and 10 days.

In the windows defined after 16 August 2020, the coefficients for *retDAX:Covid*, *retN225:Covid* and *retSS:Covid* are significant and negative for all three windows of 7, 10 and 14 days. Instead, the coefficients for *retIPAC:Covid*, and *retBND:Covid* are significant and negative for the first two windows of 7 and 10 days.

In the windows defined after 20 October 2020, the coefficients for *retSS:Covid* are significant and negative for all three windows of 7, 10 and 14 days. Instead, the coefficients for *retFTSE:Covid* are significant and negative for the first two windows of 7 and 10 days.

In the windows defined after 12 November 2020, the coefficients for *retGSPC:Covid*, *retDAX:Covid* and *retDX:Covid* are significant and negative for all three windows of 7, 10 and 14 days. Instead, the coefficients for *retFTSE:Covid*, *retURTH:Covid*, and *retIPAC:Covid* are significant and negative for the first two windows of 7 and 10 days.

In the windows defined after 14 January 2021, the coefficients for *retGSPC:Covid* are significant and negative for all three windows of 7, 10 and 14 days. Instead, the coefficients for *retN225:Covid*, *retSS:Covid*, *retEUFN:Covid*, and *retGC:Covid* are significant and negative for the first two windows of 7 and 10 days.
All the results presented above highlight the clear impact of the pandemic on Bitcoin's status as a safe haven.

We also conducted a regression analysis using dummy variables for extreme values of all index returns and the forex (FX) volatility, hence for extreme values of all our regressors without considering dummy variable for COVID-19. The multiple regression model with dummies for extreme values of FX volatility and returns of every index was defined as follows:

$$\begin{aligned} retCrypto(t) &= a_0 + (b_0 + b_1 \cdot p90_{Vol} + b_2 \cdot p95_{Vol} + b_3 \cdot p99_{Vol}) * Vol(t) + \\ &\sum_i [(c_{0,i} + c_{1,i} \cdot p10_{retIndex_i} + c_{2,i} \cdot p5_{retIndex_i} + c_{3,i} \cdot p1_{retIndex_i}) * retIndex_i(t)] + \\ &d_0 \cdot retCrypto(t-1) + e_0 \cdot Vol(t-1) + \sum_i [f_{0,i} \cdot retIndex_i(t-1)] + \epsilon(t), \end{aligned} \quad (3)$$

where

- $retCrypto$ represents the daily Bitcoin/Ether returns;
- Vol represents the volatility in the FX market;
- $p90_{Vol}$, $p95_{Vol}$, and $p99_{Vol}$ are indicator variables for days in the sample where volatility is in the 90th, 95th and 99th percentiles, respectively;
- $p10_{retIndex_i}$, $p5_{retIndex_i}$, and $p1_{retIndex_i}$ are indicator variables for days in the sample where $retIndex_i$ are in the 10th, 5th and 1th percentiles, respectively;
- r_i represents the returns of the i-th index, with i varying from 1 to 13, which is the number of indexes under study.

Results showed that all coefficients are not statistically significant, hence no indication of Bitcoin as a safe haven or hedge has been highlighted. This is in according to the results presented in work [6]. So, Bitcoin is not correlated with volatility both on average and in periods of extreme volatility, and is also uncorrelated with all other indexes under study, both on average and in the periods in which the index returns acquire extreme values.

Let us analyze the results illustrated in Tables 6 and 7, or in Table 8, which shows only the variables significant to our analysis, related to the Ether cryptocurrency as a dependent variable. Results highlighted that considerations similar to those illustrated for Bitcoin can also be conducted for this cryptocurrency, but the indications for Ether as a safe haven are smaller, contrary to results in the work by Mariana et al. [8] that analyzed a smaller market with only five indexes.

In the windows defined after 5 March 2020, the coefficients for *retDAX:Covid*, *retN225:Covid*, and *retURTH:Covid* are significant and negative for all three windows of 7, 10 and

14 days. Instead, the coefficients for *retGSPC:Covid* and *retGD:Covid* are significant and negative for the first two windows of 7 and 10 days.

In the windows defined after 16 August 2020, only the coefficients for *retSS:Covid* are significant and negative for the first two windows of 7 and 10 days.

In the windows defined after 20 October 2020, the coefficients for *retFTSE:Covid* and *retGD:Covid* are significant and negative for all three windows of 7, 10 and 14 days. Instead, the coefficients for *retBND:Covid* and *retGC:Covid* are significant and negative for the first two windows of 7 and 10 days.

In the windows defined after 12 November 2020, the coefficients for *retGSPC:Covid* and *retURTH:Covid* are significant and negative for the first two windows of 7 and 10 days.

In the windows defined after 14 January 2021, the coefficients for *retGSPC:Covid*, *retN225:Covid*, and *retSS:Covid* are significant and negative for the first two windows of 7 and 10 days.

Table 6. Summary of regression model results about Ether considering the variables with significant coefficient, for the first nine taken into account.

	5 March 2020 +			**16 August 2020 +**		
	7 Days	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**
Intercept	0	0	0.009	0.009	0.009	0.009
retGD	−0.559	−0.534	−0.653	−0.729	−0.715	−0.719
retBND	0	0	0	2.647	2.635	2.65
retBZ	0.304	0.297	0.303	0.315	0.312	0.313
retGC	0.382	0.498	0	0.509	0.504	0.507
Volatility:COVID	−12.369	−9.003	−7.867	0	0	0
retGSPC:COVID	−3.913	−2.841	0	0	−1.52	−7.591
retDAX:COVID	−5.015	−4.715	−6.593	−2.263	0	−6.063
retFTSE:COVID	4.191	4.642	0	0	0.895	6.245
retN225:COVID	−2.977	−3.77	−7.619	−3.538	−6.258	0
retSS:COVID	9.815	9.155	0	−3.221	0	−1.777
retURTH:COVID	−2.917	−2.073	−9.831	2.171	0	4.783
retEUFN:COVID	7.214	5.454	6.731	6.335	7.439	8.193
retIPAC:COVID	3.4475	3.279	0	−1.558	0	3.351
retDX:COVID	2.676	2.297	8.852	0	−2.021	−14.433
retGD:COVID	−6.513	−6.343	0	1.698	0	8.687
retBND:COVID	−4.496	0	0	−0.833	0	0
retBZ:COVID	0	0.499	0	0	0	−8.765
retGC:COVID	1.198	0	0	0	0	−2.136
retIPACprevious	0	0	−1.052	0	0	0
retBNDprevious	0	0	0	−1.349	−1.375	−1.363

Table 7. Summary of regression model results about Eth considering the variables with significant coefficient for the remaining nine taken into account.

	20 October 2020 +			12 November 2020 +			14 January 2021 +		
	7 Days	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**
Intercept	0	0	0.009	0.009	0	0.009	0	0	0
retGD	−0.716	−0.718	−0.72	−0.738	−0.744	−0.762	−0.736	−0.71	−0.708
retBND	2.6	2.6	2.575	2.592	2.613	2.588	2.649	2.663	2.685
retBZ	0.306	0.305	0.309	0.321	0.319	0.328	0.31	0.301	0.303
retGC	0.484	0.485	0.497	0.469	0.466	0.498	0.467	0.481	0.478
Volatility:COVID	0	0	0	−7.748	0	0	6.594	13.346	0
retGSPC:COVID	2.729	−1.585	−10.4	−2.021	−2.418	0	−1.72	−1.892	0
retDAX:COVID	0.712	1.728	4.912	−3.565	0	−11.217	0	2.61	0
retFTSE:COVID	−3.637	−6.845	−14.845	0	−1.862	0	0	0	0
retN225:COVID	0	5.272	0	0	0	−8.869	−9.794	−11.181	0
retSS:COVID	0	−5.569	−3.672	0	0	0	−11.794	−14.648	0
retURTH:COVID	1.725	−0.411	21.28	−1.089	−1.156	0	0	0	0
retEUFN:COVID	−1.965	1.062	−2.307	5.428	0	5.493	−3.398	0	0
retIPAC:COVID	3.07	5.742	0	−2.93	0	0	0	0	0
retDX:COVID	1.397	5.644	−2.659	−2.73	0	3.751	2.794	4.431	0
retGD:COVID	−0.772	−3.19	−34.858	1.441	2.104	22.62	0	0	0
retBND:COVID	−0.836	−3.467	18.426	3.78	0	0	2.533	3.733	0
retBZ:COVID	0	2.996	14.876	0	0.605	−7.042	7.172	9.067	0
retGC:COVID	−4.204	−1.585	5.196	4.237	4.99	0	0	0	0
retIPACprevious	0	0	0	0	0	0	0	0	0
retBNDprevious	−1.327	−1.328	−1.352	−1.337	−1.335	−1.29	−1.428	−1.439	−1.463

Table 8. Summary of regression model results about Eth considering only the variables with significant coefficients for our analysis.

	5 March 2020 +			16 August 2020 +		
	7 Days	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**
retGD	−0.559	−0.534	−0.653	−0.729	−0.715	−0.719
retGSPC:COVID	−3.913	−2.841	0	0	−1.52	−7.591
retDAX:COVID	−5.015	−4.715	−6.593	−2.263	0	−6.063
retN225:COVID	−2.977	−3.77	−7.619	−3.538	−6.258	0
retURTH:COVID	−2.917	−2.073	−9.831	2.171	0	4.783
retGD:COVID	−6.513	−6.343	0	1.698	0	8.687
retBNDprevious	0	0	0	−1.349	−1.375	−1.363

	20 October 2020 +			12 November 2020 +			14 January 2021 +		
	7 Days	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**	**7 Days**	**10 Days**	**14 Days**
retGD	−0.716	−0.718	−0.72	−0.738	−0.744	−0.762	−0.736	−0.71	−0.708
retGSPC:COVID	2.729	−1.585	−10.4	−2.021	−2.418	0	−1.72	−1.892	0
retFTSE:COVID	−3.637	−6.845	−14.845	0	−1.862	0	0	0	0
retN225:COVID	0	5.272	0	0	0	−8.869	−9.794	−11.181	0
retSS:COVID	0	−5.569	−3.672	0	0	0	−11.794	−14.648	0
retURTH:COVID	1.725	−0.411	21.28	−1.089	−1.156	0	0	0	0
retGD:COVID	−0.772	−3.19	−34.858	1.441	2.104	22.62	0	0	0
retBND:COVID	−0.836	−3.467	18.426	3.78	0	0	2.533	3.733	0
retGC:COVID	−4.204	−1.585	5.196	4.237	4.99	0	0	0	0
retBNDprevious	−1.327	−1.328	−1.352	−1.337	−1.335	−1.29	−1.428	−1.439	−1.463

These results also give some indications of a safe haven for Ether, which in the windows of 7 and 10 days of the last individuated date (14 January 2021) is linked positively with the volatility in the FX market. The coefficients for the variable *Volatility:Covid* are significant and positive for the first two windows of 7 and 10 days.

3.2.2. DCC Model Results: Dynamic Conditional Correlations

Before proceeding with the results analysis of the DCC model let us describe all the performed tests and analyses to resolve such a model.

First of all we performed normality tests to confirm that the returns were non-normal and heteroscedastic data needed to be handled through GARCH models. Specifically, the Henze–Zirkler test, which is a multivariate normality test, and the Anderson–Darling test, which is a univariate normality test, were run. Both the first test statistics on the entire sample and the second test statistics on the univariate series concluded that the null hypothesis was rejected. So both the univariate samples and the multivariate sample are not normally distributed as expected from the financial time series.

In addition, a test to evaluate the presence of a dynamic structure in the correlations was performed. The test confirmed the presence of a dynamic structure, so a DCC-GARCH model was estimated. The DCC-GARCH model chosen was a DCC-eGARCH(1,1), where eGARCH stands for exponentional GARCH. In this model the volatility is computes as follows:

$$ln(h_t) = \omega + \beta ln(h_{t-1}) + \alpha \left(\frac{|\epsilon_{t-i}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right) + \gamma \frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}})). \tag{4}$$

The choice was based on the AIC and BIC scores varying the order of the ARMA-GARCH model and the type of GARCH model.

For the DCC-eGARCH(1,1) model the most of the parameters are significant, therefore we can conclude that the chosen model accurately captures both the univariate structure of the indexes and their interactions (see Table 9).

Table 9. Optimal parameters.

	Estimate	Std. Error	t Value	Pr (>∣t∣)
$[000002.SS].\omega$	−1.542860	1.443807	−1.0686	0.285248
$[000002.SS].\alpha1$	−0.068448	0.128806	-5.3141×10^{-1}	0.595138
$[000002.SS].\beta1$	0.819270	0.167389	4.8944	0.000001
$[000002.SS].\gamma1$	0.493105	0.295964	1.6661	0.095693
$[EUFN].\omega$	−0.245042	0.096110	−2.5496	0.010785
$[EUFN].\alpha1$	−0.170790	0.056476	−3.0241	0.002494
$[EUFN].\beta1$	0.966439	0.012148	$7.9557\times10^{+1}$	0.000000
$[EUFN].\gamma1$	0.234274	0.052733	4.4426	0.000009
$[IPAC].\omega$	−0.210337	0.068830	−3.0559	0.002244
$[IPAC].\alpha1$	−0.125786	0.049631	−2.5344	0.011264
$[IPAC].\beta1$	0.974251	0.007748	$1.2574\times10^{+2}$	0.000000
$[IPAC].\gamma1$	0.262762	0.082990	3.1662	0.001545
$[DX-Y.NYB].\omega$	−0.059457	0.027381	−2.1714	0.029897
$[DX-Y.NYB].\alpha1$	−0.041247	0.024270	−1.6995	0.089231
$[DX-Y.NYB].\beta1$	0.994205	0.002453	$4.0529\times10^{+2}$	0.000000
$[DX-Y.NYB].\gamma1$	0.177653	0.034066	5.2149	0.000000
$[GC=F].\omega$	−1.470428	0.828544	−1.7747	0.075945
$[GC=F].\alpha1$	0.104286	0.088503	1.1783	0.238664
$[GC=F].\beta1$	0.824632	0.097232	8.4811	0.000000
$[GC=F].\gamma1$	0.525887	0.192437	2.7328	0.006280

Table 9. *Cont.*

	Estimate	Std. Error	t Value	Pr (>|t|)
$[DAX].\omega$	−0.177843	0.082192	−2.1637	0.030484
$[DAX].\alpha1$	−0.132051	0.048471	−2.7243	0.006443
$[DAX].\beta1$	0.976456	0.009049	1.0790×10^{2}	0.000000
$[DAX].\gamma1$	0.209744	0.068337	3.0693	0.002146
$[\hat{}GSPC].\omega$	−0.634528	0.354695	−1.7889	0.073624
$[\hat{}GSPC].\alpha1$	−0.137234	0.114002	−1.2038	0.228672
$[\hat{}GSPC].\beta1$	0.922111	0.042674	2.1608×10	0.000000
$[\hat{}GSPC].\gamma1$	0.455469	0.135636	3.3580	0.000785
$[\hat{}FTSE].\omega$	−0.426567	0.081726	−5.2195	0.000000
$[\hat{}FTSE].\alpha1$	−0.175619	0.046570	−3.7710	0.000163
$[\hat{}FTSE].\beta1$	0.949165	0.009356	1.0145×10^{2}	0.000000
$[\hat{}FTSE].\gamma1$	0.152212	0.058722	2.5921	0.009541
$[\hat{}N225].\omega$	−0.528630	0.141238	−3.7428	0.000182
$[\hat{}N225].\alpha1$	−0.237799	0.055749	−4.2655	0.000020
$[\hat{}N225].\beta1$	0.939065	0.015363	6.1124×10	0.000000
$[\hat{}N225].\gamma1$	0.266471	0.063192	4.2168	0.000025
$[BTC-USD].\omega$	−0.552653	0.485819	−1.1376	0.255300
$[BTC-USD].\alpha1$	−0.082472	0.168872	-4.8837×10^{-1}	0.625290
$[BTC-USD].\beta1$	0.900147	0.094514	9.5239	0.000000
$[BTC-USD].\gamma1$	0.197932	0.308051	6.4253×10^{-1}	0.520530
$[ETH-USD].\omega$	−0.504108	0.908202	-5.5506×10^{-1}	0.578852
$[ETH-USD].\alpha1$	−0.028082	0.220747	-1.2721×10^{-1}	0.898771
$[ETH-USD].\beta1$	0.898401	0.190023	4.7278	0.000002
$[ETH-USD].\gamma1$	0.213930	0.488293	4.3812×10^{-1}	0.661301
$[URTH].\omega$	−0.370244	0.136078	−2.7208	0.006512
$[URTH].\alpha1$	−0.130324	0.081318	−1.6026	0.109013
$[URTH].\beta1$	0.953897	0.016009	5.9586×10	0.000000
$[URTH].\gamma1$	0.342878	0.079368	4.3201	0.000016
$[BND].\omega$	−0.242602	0.159616	−1.5199	0.128533
$[BND].\alpha1$	−0.007477	0.070278	-1.0639×10^{-1}	0.915270
$[BND].\beta1$	0.975701	0.013120	7.4367×10	0.000000
$[BND].\gamma1$	0.601597	0.144888	4.1521	0.000033
$[BZ].\omega$	−0.086342	0.004638	-1.8617×10	0.000000
$[BZ].\alpha1$	−0.192312	0.034443	−5.5834	0.000000
$[BZ].\beta1$	0.990628	0.000019	5.2568×10^{4}	0.000000
$[BZ].\gamma1$	0.070036	0.013730	5.1008	0.000000
$[GD].\omega$	−0.176354	0.005567	-3.1676×10	0.000000
$[GD].\alpha1$	−0.170768	0.031154	−5.4814	0.000000
$[GD].\beta1$	0.980731	0.000005	1.9745×10^{5}	0.000000
$[GD].\gamma1$	0.055332	0.013251	4.1758	0.000030
$[Joint]dcca1$	0.018359	0.005080	3.6136	0.000302
$[Joint]dccb1$	0.853105	0.026664	3.1995×10	0.000000

To confirm that the chosen DCC-eGARCH(1,1) model accurately captured the interactions among the indexes, the Weighted Ljung–Box test on standardized residuals and on standardized squared residuals of the estimated univariate GARCH(1,1) models was executed. The tests' statistics confirm that the residuals and squared residuals are uncorrelated. All the p-values are greater than 0.05, so the null hypothesis of no serial correlation is never rejected (results are available upon request).

Choosing the DCC-eGARCH(1,1) model, we proceeded with the computation of the dynamic conditional correlations. Tables 10–13 describe some statistics of these correlations related to the pairs Bitcoin/Ether indexes. Precisely, the median, the minimum and the maximum of the dynamic correlation between the pairs Bitcoin/Ether indexes are shown in six time windows. The first time window is the time-interval range between 1 July 2019 and 4 March 2020. Hence, it is the time window preceding the start of the pandemic. The other five time windows correspond to the *event windows* fourteen days long during the

COVID-19 pandemic. This to investigate the trend of the correlations in the same windows in which we solved the regression model described in the previous sections.

The statistics, shown in the Tables (look at the underlined correlations), highlight that some pairwise correlations, in some *event windows* during the COVID-19 pandemic, were slightly lower or more negative than those in the period pre-pandemic, named *July- March 4* in the Tables. In addition, there is also some correspondence between these correlations' values and the trend highlighted through the previously described regression analysis.

For example, for the returns of the SSE A Share Index (*retSS* variable) the median values computed in the 16 August +14, and 14 January +14 *event windows* (0.1191 and 0.0314, respectively) are slightly lower than the median computed in the *July-March 4* time window (0.1194). Additionally, the maximum values of the correlation computed in the 16 August +14, 20 October +14, and 14 January +14 *event windows* (0.1262, 0.1456, and 0.1474, respectively) are slightly lower than the maximum value computed in the *July-March 4* time window (0.2078). All this agrees with the results of the regression model, which gives indications of safe haven for Bitcoin in the same *event windows* against the downward movement of the SSE A Share Index, in the three *event windows* defined around 16 August 2020 and 20 October 2020 dates, and in the first two *event windows* defined around 14 January 2021 date (the coefficients of the *retSS:COVID* variable, in the intervals just mentioned, are all negative).

Table 10. Statistics of dynamic conditional correlations between the pairs Bitcoin and stock indexes.

		SS	**EUFN**	**IPAC**	**DX**	**GC**	**DAX**	**GSPC**	**FTSE**	**N225**
July-March 4	min	−0.0203	0.0525	−0.0020	−0.2559	0.0871	0.0248	0.0157	0.0033	−0.0656
	median	0.1194	0.1428	0.1737	−0.1552	0.2408	0.1747	0.1548	0.1369	0.0273
	max	0.2078	0.2674	0.2177	−0.1131	0.2903	0.2465	0.2379	0.1972	0.0680
5 March +14	min	0.1296	0.1543	0.1897	−0.2105	0.2190	0.1842	0.1685	0.1380	0.0494
	median	0.2271	0.2704	0.2884	−0.1785	0.2295	0.2935	0.2511	0.2548	0.1512
	max	0.2854	0.4040	0.4634	−0.0463	0.4127	0.4100	0.3662	0.4093	0.1988
16 August +14	min	0.0841	0.1104	0.1698	−0.2213	0.2723	0.1581	0.1498	0.0996	0.0161
	median	<u>0.1191</u>	<u>0.1316</u>	0.1859	−0.1904	0.2802	0.1785	0.1582	<u>0.1331</u>	<u>0.0266</u>
	max	<u>0.1262</u>	<u>0.1474</u>	0.1931	−0.1802	0.3017	0.1879	0.1657	<u>0.1518</u>	<u>0.0327</u>
20 October +14	min	0.1136	0.1378	0.1996	−0.2240	0.2716	0.1607	0.1499	0.0982	0.0406
	median	0.1228	0.1550	0.2129	−0.2094	0.2768	0.1812	0.1690	<u>0.1309</u>	0.0503
	max	<u>0.1456</u>	<u>0.1824</u>	0.2260	−0.1983	0.2885	0.1951	0.1787	<u>0.1494</u>	0.0643
12 November +14	min	0.1353	0.1380	0.2056	−0.2307	0.2045	0.1794	0.1545	0.1410	0.0507
	median	0.1407	0.1482	0.2173	−0.2089	0.2767	0.1912	0.1720	0.1469	0.0706
	max	<u>0.1579</u>	<u>0.1670</u>	0.2470	−0.1895	0.3056	0.2106	0.2014	0.1560	0.0777
14 January +14	min	−0.0298	0.1179	0.1949	−0.1678	0.1850	0.2015	0.1534	0.2003	0.0394
	median	<u>0.0314</u>	0.1546	0.2105	−0.1313	<u>0.2246</u>	0.2263	0.1606	0.2260	0.0533
	max	<u>0.1474</u>	<u>0.1649</u>	0.2339	−0.1110	<u>0.2396</u>	0.2794	0.1995	0.2824	0.0900

Table 11. Statistics of dynamic conditional correlations between the pairs Bitcoin and the remaining stock indexes.

	MEDIAN	BTC	ETH	URTH	BND	BZ	GD
July-March 4	min	1	0.782	0.052	0.004	−0.071	−0.043
	median	1	0.846	0.186	0.120	0.096	0.118
	max	1	0.883	0.267	0.220	0.162	0.212
5 March +14	min	1	0.841	0.194	0.106	0.102	0.132
	median	1	0.859	0.281	0.123	0.237	0.241
	max	1	0.930	0.394	0.436	0.298	0.301
16 August +14	min	1	0.820	0.179	0.122	0.100	0.140
	median	1	0.830	0.192	0.131	0.111	0.149
	max	1	0.837	0.198	0.142	0.115	0.161
20 October +14	min	1	0.835	0.176	0.118	0.079	0.128
	median	1	0.839	0.195	0.132	0.110	0.146
	max	1	0.845	0.213	0.140	0.138	0.179
12 November +14	min	1	0.801	0.192	0.147	0.100	0.136
	median	1	0.814	0.205	0.161	0.107	0.144
	max	1	0.829	0.230	0.167	0.145	0.169
14 January +14	min	1	0.809	0.185	0.074	−0.019	−0.039
	median	1	0.835	0.196	0.121	<u>0.079</u>	<u>0.083</u>
	max	1	0.842	0.226	<u>0.147</u>	<u>0.097</u>	<u>0.116</u>

Table 12. Statistics of dynamic conditional correlations between the pairs Ether and stock indexes.

	MEDIAN	SS	EUFN	IPAC	DX	GC	DAX	GSPC	FTSE	N225
July-March 4	min	−0.0584	0.1002	−0.0268	−0.2499	0.0212	0.0367	0.0077	0.0117	−0.0468
	median	0.1153	0.1939	0.2051	−0.1668	0.1778	0.2114	0.1863	0.1178	0.0971
	max	0.1556	0.3056	0.2399	−0.0745	0.2148	0.2659	0.2492	0.1729	0.1677
5 March +14	min	0.1170	0.2037	0.2007	−0.2216	0.1575	0.2190	0.1903	0.1094	0.1004
	median	0.2084	0.3070	0.2985	−0.1760	0.1656	0.3205	0.2692	0.2260	0.1987
	max	0.2760	0.4285	0.4686	−0.0747	0.3693	0.4306	0.3794	0.3887	0.2376
16 August +14	min	0.0826	0.1641	0.2082	−0.2212	0.1897	0.2051	0.1777	0.0810	0.0866
	median	<u>0.1043</u>	<u>0.1865</u>	0.2139	−0.2039	0.1987	0.2161	<u>0.1833</u>	<u>0.0980</u>	0.1111
	max	<u>0.1227</u>	<u>0.2082</u>	0.2231	−0.1927	0.2177	<u>0.2367</u>	<u>0.1975</u>	<u>0.1301</u>	0.1266
20 October +14	min	0.1135	0.2169	0.2441	−0.2607	0.2019	0.2361	0.2063	0.1098	0.1021
	median	0.1210	0.2254	0.2510	−0.2208	0.2087	0.2483	0.2184	0.1332	0.1097
	max	0.1500	0.2537	0.2622	−0.2132	0.2505	0.2639	0.2248	0.1412	0.1183
12 November +14	min	0.1062	0.1763	0.2121	−0.2129	0.0068	0.2205	0.1738	0.1174	0.0906
	median	0.1126	<u>0.1882</u>	0.2230	−0.2000	0.2029	0.2329	0.2047	0.1239	0.1076
	max	0.1626	<u>0.2890</u>	0.2806	−0.1880	0.2115	0.2627	0.2311	0.1593	0.1795
14 January +14	min	0.0574	0.1440	0.1860	−0.1984	0.1878	0.2091	0.1279	0.1530	0.0756
	median	0.0708	<u>0.1785</u>	0.2138	−0.1502	0.2104	0.2344	<u>0.1687</u>	0.1724	0.1071
	max	0.1706	<u>0.1972</u>	0.2378	−0.1388	0.2361	0.2639	<u>0.2056</u>	0.2200	0.1328

Table 13. Statistics of dynamic conditional correlations between the pairs Ether and the remaining stock indexes.

	MEDIAN	**BTC**	**ETH**	B	**BND**	**BZ**	**GD**
July-March 4	min	0.782	1	0.052	−0.020	−0.075	−0.055
	median	0.846	1	0.226	0.111	0.144	0.157
	max	0.883	1	0.295	0.244	0.229	0.252
5 March +14	min	0.841	1	0.227	0.099	0.114	0.133
	median	0.859	1	0.310	0.131	0.253	0.252
	max	0.930	1	0.415	0.428	0.292	0.290
16 August+14	min	0.820	1	0.225	0.052	0.122	0.165
	median	0.830	1	0.229	<u>0.081</u>	<u>0.138</u>	0.170
	max	0.837	1	0.243	<u>0.112</u>	<u>0.153</u>	0.184
20 October +14	min	0.835	1	0.247	0.113	0.141	0.169
	median	0.839	1	0.257	0.131	0.168	0.188
	max	0.845	1	0.269	0.151	0.189	0.218
12 November +14	min	0.801	1	0.223	0.082	0.125	0.140
	median	0.814	1	0.244	0.130	0.129	0.145
	max	0.829	1	0.279	0.145	0.269	0.261
14 January +14	min	0.809	1	0.176	0.115	0.041	0.030
	median	0.835	1	<u>0.214</u>	0.133	<u>0.120</u>	<u>0.122</u>
	max	0.842	1	<u>0.241</u>	0.160	<u>0.148</u>	<u>0.154</u>

4. Discussion and Conclusions

During the COVID 19 pandemic, the price of Bitcoin underwent large fluctuations from around USD 10 to around USD 4100 in the first quarter of 2020, and now, at the time of writing (22 February 2021) it stands at around USD 48,000. Many have wondered if Bitcoin is a safe haven and if this cryptocurrency will become a store of value. This is also the research question of our work.

By performing a regression analysis, we studied the safe-haven properties of Bitcoin against losses of the major stock market indices, oil, gold, general commodity index and US dollar index. We performed the regression analysis using dummy variables defined around the COVID-19 pandemic events. In addition, a dynamic conditional correlation analysis based on the DCC-Garch model was performed to try giving more robust results.

The results suggest the COVID-19 pandemic has impacted Bitcoin's status as a safe haven. They highlight negative relations between the movements of the Bitcoin returns and those of some financial indexes that do not emerge studying the model without considering the COVID-19 event. The same considerations can be made for Ether. So for this last cryptocurrency, a negative relation between the movements of its returns and those of some financial indexes can also be highlighted. All this emerges studying the regression model around fifteen *event windows* within which crucial events linked to the COVID-19 spread have been individuated. In many *event windows*, the coefficients of some interaction terms, formed by the dummy variable *Covid* (set to 1 in the *event window*), and by a variable representing a financial index, are statistically significant and negative, showing effects of safe haven for these two cryptocurrencies against downward movements of the indexes taken into account. The coefficient of the interaction term, composed of the variable *Vol*, representing the volatility in the FX market, and the dummy variable *Covid* does not emphasize effects of safe haven for Bitcoin and Ether against the movements of the *Volatility*. It always is negative, but for Ether in the three *event windows* defined around the 14 January +14 date.

It is worth underlining that safe-haven assets generally have some specific characteristics. The activity related to them must be easily convertible into cash at any time. The growth in supply must never exceed the demand. The assets are unlikely to become obsolete or replaced, and must not degrade or deteriorate over time. The supply of Bitcoin is stuck at 21 million, an amount that should be reached in 2040. This should help to increase the price of Bitcoin, and belief in its properties as a safe haven like gold, to which it is often equated. In general, safe havens are instruments guaranteed by entities; for example, by the governments of the most developed countries whose credibility is indisputable. The widespread opinion is that these entities will always be solvent and will never go bankrupt.

To be a safe-haven asset, Bitcoin needs a clear, solid regulation that is valid globally. This would increase confidence in Bitcoin and develop the market. Additionally, many have heard of cryptocurrency but do not know how to use it, to spend it and to acquire it. Even if the mechanisms of the blockchain system are not known, as happens with the fiat currency system in which most people do not know central banks and monetary policies, it must, however, be clear how to spend the currency and how to get hold of it.

The regression model and dynamic conditional correlation analysis performed in this paper highlight how, during the COVID-19 pandemic, the relations between Bitcoin and some financial indexes showed the first insights of safe haven for Bitcoin against downward movements of some stocks' indexes.

As in the literature, our work also does not define Bitcoin as a safe haven regardless but always under very specific circumstances, with time intervals, country economy, crisis period and financial stocks taken into account. The COVID-19 pandemic impacted Bitcoin, and in this period Bitcoin provided safe haven features to investors, but Bitcoin is still far from being defined a safe-haven asset. So the very first insights of Bitcoin as a safe haven emerge, but we are far from the insights that would make Bitcoin a safe haven investment par excellence like gold is.

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Appendix A

Table A1. Summary of regression model results about Btc considering the window of 7 days around 5 March 2020 date.

	Coef.	Std. Err.	t	P > |t|	[0.025	0.975]
Intercept	0.000519	0.003235	0.160574	8.724870×10^{-1}	−0.005835	0.006873
Volatility	1.861958	1.541440	1.207934	2.275854×10^{-1}	−1.165789	4.889704
retGSPC	0.377757	0.867966	0.435221	6.635703×10^{-1}	−1.327129	2.082644
retDAX	0.054629	0.231717	0.235759	8.137063×10^{-1}	−0.400516	0.509775
retFTSE	−0.164595	0.162726	−1.011489	3.122216×10^{-1}	−0.484226	0.155036
retN225	−0.388537	0.153034	−2.538898	1.139119×10^{-2}	−0.689130	−0.087943
retSS	−0.002224	0.132412	−0.016799	9.866029×10^{-1}	−0.262312	0.257863
retMWL	−0.486956	1.201786	−0.405194	6.854905×10^{-1}	−2.847543	1.873630
retEUFN	−0.116213	0.205816	−0.564643	5.725437×10^{-1}	−0.520484	0.288058
retIPAC	1.049704	0.481604	2.179599	2.970528×10^{-2}	0.103722	1.995687
retDX	0.052456	0.820777	0.063911	9.490644×10^{-1}	−1.559741	1.664653
retGD	−0.406932	0.205612	−1.979126	4.829388×10^{-2}	−0.810802	−0.003062
retBND	0.415287	0.473071	0.877855	3.804011×10^{-1}	−0.513933	1.344507
retBZ	0.249528	0.094420	2.642729	8.455474×10^{-3}	0.064064	0.434991
retGC	0.420767	0.173198	2.429406	1.543873×10^{-2}	0.080567	0.760968
Volatility:COVID	−8.046328	2.059425	−3.907076	1.049045×10^{-4}	−12.091516	−4.001140
retGSPC:COVID	−2.791220	0.511730	−5.454480	7.396082×10^{-8}	−3.796376	−1.786064
retDAX:COVID	−4.026278	0.951215	−4.232773	2.699539×10^{-5}	−5.894685	−2.157870
retFTSE:COVID	4.366916	1.267722	3.444696	6.147459×10^{-4}	1.876816	6.857017
retN225:COVID	−1.886215	0.653011	−2.888490	4.021499×10^{-3}	−3.168880	−0.603550
retSS:COVID	7.313847	1.156698	6.323037	5.264541×10^{-10}	5.041823	9.585871
retMWL:COVID	−2.224790	0.459455	−4.842235	1.665634×10^{-6}	−3.127266	−1.322313
retEUFN:COVID	4.951871	1.071813	4.620088	4.769613×10^{-6}	2.846581	7.057160
retIPAC:COVID	2.815130	0.495212	5.684698	2.116044×10^{-8}	1.842419	3.787841
retDX:COVID	2.258807	0.590198	3.827198	1.442955×10^{-4}	1.099520	3.418093
retGD:COVID	−4.745632	0.894099	−5.307724	1.605368×10^{-7}	−6.501851	−2.989414
retBND:COVID	−3.526005	0.947553	−3.721168	2.184281×10^{-4}	−5.387219	−1.664790
retBZ:COVID	0.115045	0.120629	0.953707	3.406456×10^{-1}	−0.121899	0.351989
retGC:COVID	0.837573	0.212477	3.941947	9.111532×10^{-5}	0.420219	1.254927
retGSPCprevious	0.317137	0.630108	0.503306	6.149479×10^{-1}	−0.920541	1.554816
retDAXprevious	−0.215440	0.226793	−0.949938	3.425558×10^{-1}	−0.660915	0.230035
retFTSEprevious	0.299326	0.205157	1.459010	1.451261×10^{-1}	−0.103650	0.702303
retN225previous	0.021541	0.173923	0.123853	9.014763×10^{-1}	−0.320085	0.363167
retSSprevious	0.151231	0.162394	0.931259	3.521233×10^{-1}	−0.167749	0.470211
retMWLprevious	−0.465460	0.794070	−0.586170	5.579986×10^{-1}	−2.025199	1.094278
retEUFNprevious	0.144767	0.210160	0.688842	4.912098×10^{-1}	−0.268036	0.557569
retIPACprevious	−0.147313	0.344129	−0.428075	6.687616×10^{-1}	−0.823262	0.528636
retDXprevious	−1.003056	0.532647	−1.883154	6.020031×10^{-2}	−2.049297	0.043186
retGDprevious	0.241955	0.297856	0.812323	4.169535×10^{-1}	−0.343103	0.827014
retBNDprevious	0.274211	0.699812	0.391836	6.953296×10^{-1}	−1.100382	1.648805
retBZprevious	0.008309	0.145255	0.057203	9.544039×10^{-1}	−0.277005	0.293623
retGCprevious	−0.063186	0.158377	−0.398959	6.900765×10^{-1}	−0.374274	0.247903
Volatilityprevious	−1.138806	1.868439	−0.609496	5.424443×10^{-1}	−4.808854	2.531242
retBTCprevious	0.011939	0.046409	0.257247	7.970828×10^{-1}	−0.079220	0.103098

Table A2. Summary of regression model results about Btc considering the window of 10 days around 5 March 2020 date.

	Coef.	Std. Err.	t	P > |t|	[0.025	0.975]
Intercept	0.000504	0.003202	0.157274	8.750859×10^{-1}	−0.005785	0.006793
Volatility	1.564366	1.586767	0.985883	3.246196×10^{-1}	−1.552425	4.681157
retGSPC	0.364230	0.876243	0.415673	6.778100×10^{-1}	−1.356921	2.085381
retDAX	0.112108	0.231686	0.483881	6.286611×10^{-1}	−0.342978	0.567195
retFTSE	−0.158049	0.163666	−0.965684	3.346221×10^{-1}	−0.479528	0.163429
retN225	−0.322226	0.155915	−2.066680	3.922673×10^{-2}	−0.628480	−0.015972
retSS	−0.012323	0.131195	−0.093930	9.251984×10^{-1}	−0.270021	0.245374
retMWL	−0.605373	1.221744	−0.495499	6.204434×10^{-1}	−3.005172	1.794425
retEUFN	−0.152120	0.211782	−0.718289	4.728806×10^{-1}	−0.568110	0.263869
retIPAC	1.028862	0.475740	2.162655	3.099333×10^{-2}	0.094394	1.963329
retDX	−0.105613	0.819252	−0.128914	8.974727×10^{-1}	−1.714820	1.503595
retGD	−0.391464	0.211626	−1.849788	6.487452×10^{-2}	−0.807149	0.024221
retBND	−0.124085	0.582607	−0.212983	8.314186×10^{-1}	−1.268465	1.020294
retBZ	0.244991	0.095985	2.552381	1.096512×10^{-2}	0.056453	0.433530
retGC	0.485437	0.189116	2.566879	1.052235×10^{-2}	0.113969	0.856906
Volatility:COVID	−5.960112	1.532135	−3.890068	1.123477×10^{-4}	−8.969593	−2.950630
retGSPC:COVID	−2.096716	0.595851	−3.518858	4.688855×10^{-4}	−3.267110	−0.926321
retDAX:COVID	−3.886193	0.978315	−3.972332	8.053458×10^{-5}	−5.807839	−1.964547
retFTSE:COVID	4.670566	1.221398	3.823952	1.461876×10^{-4}	2.271448	7.069684
retN225:COVID	−2.474954	0.615900	−4.018433	6.665593×10^{-5}	−3.684730	−1.265178
retSS:COVID	6.953559	1.246511	5.578416	3.794038×10^{-8}	4.505112	9.402006
retMWL:COVID	−1.681220	0.540890	−3.108251	1.978209×10^{-3}	−2.743657	−0.618784
retEUFN:COVID	3.804935	1.242417	3.062527	2.300945×10^{-3}	1.364531	6.245340
retIPAC:COVID	2.716392	0.522868	5.195174	2.875442×10^{-7}	1.689353	3.743431
retDX:COVID	2.033804	0.629049	3.233141	1.296952×10^{-3}	0.798201	3.269407
retGD:COVID	−4.679026	0.920970	−5.080540	5.146648×10^{-7}	−6.488032	−2.870020
retBND:COVID	−1.748613	1.294075	−1.351246	1.771663×10^{-1}	−4.290487	0.793260
retBZ:COVID	0.315101	0.186865	1.686248	9.230909×10^{-2}	−0.051947	0.682149
retGC:COVID	0.233600	0.138870	1.682148	9.310162×10^{-2}	−0.039174	0.506373
retGSPCprevious	0.319588	0.631889	0.505766	6.132213×10^{-1}	−0.921594	1.560770
retDAXprevious	−0.190991	0.228979	−0.834096	4.045853×10^{-1}	−0.640761	0.258779
retFTSEprevious	0.401148	0.225330	1.780268	7.557806×10^{-2}	−0.041454	0.843750
retN225previous	0.068619	0.173269	0.396022	6.922404×10^{-1}	−0.271724	0.408961
retSSprevious	0.135488	0.163490	0.828722	4.076171×10^{-1}	−0.185646	0.456622
retMWLprevious	−0.479158	0.804985	−0.595239	5.519260×10^{-1}	−2.060343	1.102026
retEUFNprevious	0.068363	0.224509	0.304498	7.608623×10^{-1}	−0.372627	0.509352
retIPACprevious	−0.205606	0.342797	−0.599788	5.488917×10^{-1}	−0.878942	0.467730
retDXprevious	−1.196388	0.547880	−2.183668	2.940391×10^{-2}	−2.272556	−0.120220
retGDprevious	0.230030	0.295055	0.779617	4.359478×10^{-1}	−0.349528	0.809588
retBNDprevious	0.387602	0.697597	0.555625	5.786907×10^{-1}	−0.982645	1.757850
retBZprevious	0.015779	0.144608	0.109112	9.131527×10^{-1}	−0.268267	0.299824
retGCprevious	−0.095305	0.158211	−0.602390	5.471599×10^{-1}	−0.406069	0.215460
Volatilityprevious	−0.822011	1.875311	−0.438333	6.613150×10^{-1}	−4.505572	2.861550
retBTCprevious	0.015492	0.045447	0.340874	7.333271×10^{-1}	−0.073777	0.104760

Table A3. Summary of regression model results about Btc considering the window of 14 days around 5 March 2020 date.

	Coef.	Std. Err.	t	P > |t|	[0.025	0.975]
Intercept	0.003136	0.003020	1.038462	2.995096×10^{-1}	−0.002796	0.009069
Volatility	2.473335	1.501963	1.646735	1.001816×10^{-1}	−0.476926	5.423596
retGSPC	0.661160	0.854585	0.773662	4.394620×10^{-1}	−1.017477	2.339796
retDAX	0.032903	0.225642	0.145821	8.841162×10^{-1}	−0.410319	0.476125
retFTSE	−0.088266	0.169680	−0.520189	6.031403×10^{-1}	−0.421564	0.245032
retN225	−0.243043	0.150489	−1.615018	1.068782×10^{-1}	−0.538644	0.052559
retSS	0.036939	0.126067	0.293008	7.696264×10^{-1}	−0.210692	0.284569
retMWL	−0.804726	1.214789	−0.662441	5.079649×10^{-1}	−3.190901	1.581448
retEUFN	−0.235210	0.203292	−1.157005	2.477707×10^{-1}	−0.634531	0.164111
retIPAC	0.984459	0.471158	2.089445	3.712489×10^{-2}	0.058977	1.909941
retDX	−1.101105	0.627465	−1.754845	7.984056×10^{-2}	−2.333617	0.131407
retGD	−0.533877	0.194313	−2.747517	6.201094×10^{-3}	−0.915560	−0.152195
retBND	0.246686	0.724690	0.340402	7.336836×10^{-1}	−1.176802	1.670173
retBZ	0.252458	0.090762	2.781538	5.595128×10^{-3}	0.074177	0.430739
retGC	0.383169	0.194444	1.970584	4.927072×10^{-2}	0.001228	0.765110
Volatility:COVID	−4.794005	1.633103	−2.935520	3.468585×10^{-3}	−8.001861	−1.586149
retGSPC:COVID	0.374376	5.650599	0.066254	9.471994×10^{-1}	−10.724931	11.473683
retDAX:COVID	−6.020478	0.573694	−10.494229	1.292720×10^{-23}	−7.147369	−4.893587
retFTSE:COVID	2.123797	1.419015	1.496670	1.350507×10^{-1}	−0.663533	4.911128
retN225:COVID	−3.968531	2.686725	−1.477089	1.402221×10^{-1}	−9.245986	1.308924
retSS:COVID	2.726836	2.172040	1.255426	2.098553×10^{-1}	−1.539639	6.993311
retMWL:COVID	−11.184234	2.270737	−4.925376	1.114212×10^{-6}	−15.644577	−6.723891
retEUFN:COVID	6.123195	0.979607	6.250666	8.182700×10^{-10}	4.198982	8.047408
retIPAC:COVID	7.072823	5.141969	1.375509	1.695317×10^{-1}	−3.027396	17.173043
retDX:COVID	9.808108	2.896512	3.386179	7.591707×10^{-4}	4.118575	15.497641
retGD:COVID	1.556603	3.084781	0.504607	6.140361×10^{-1}	−4.502742	7.615948
retBND:COVID	4.711567	2.331925	2.020463	4.381780×10^{-2}	0.131035	9.292098
retBZ:COVID	−0.312265	1.541516	−0.202570	8.395460×10^{-1}	−3.340219	2.715690
retGC:COVID	5.180426	2.558226	2.025007	4.334745×10^{-2}	0.155377	10.205475
retGSPCprevious	0.554400	0.607255	0.912960	3.616620×10^{-1}	−0.638414	1.747214
retDAXprevious	−0.247877	0.226827	−1.092802	2.749576×10^{-1}	−0.693426	0.197673
retFTSEprevious	0.406215	0.215546	1.884587	6.001074×10^{-2}	−0.017175	0.829606
retN225previous	0.230483	0.140987	1.634789	1.026635×10^{-1}	−0.046453	0.507419
retSSprevious	0.042205	0.138882	0.303893	7.613242×10^{-1}	−0.230597	0.315007
retMWLprevious	−0.345948	0.786791	−0.439695	6.603304×10^{-1}	−1.891419	1.199523
retEUFNprevious	0.028105	0.220973	0.127188	8.988381×10^{-1}	−0.405946	0.462156
retIPACprevious	−0.525621	0.273759	−1.920011	5.537157×10^{-2}	−1.063359	0.012117
retDXprevious	−1.581393	0.528977	−2.989528	2.918576×10^{-3}	−2.620448	−0.542338
retGDprevious	−0.005143	0.233857	−0.021991	9.824634×10^{-1}	−0.464501	0.454215
retBNDprevious	−0.193969	0.783818	−0.247467	8.046392×10^{-1}	−1.733600	1.345662
retBZprevious	0.141724	0.105926	1.337956	1.814618×10^{-1}	−0.066343	0.349791
retGCprevious	−0.041833	0.162991	−0.256659	7.975378×10^{-1}	−0.361992	0.278326
Volatilityprevious	−2.751986	1.602243	−1.717584	8.643344×10^{-2}	−5.899225	0.395253
retBTCprevious	0.009342	0.047016	0.198694	8.425755×10^{-1}	−0.083010	0.101693

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