Relationship and causality between cryptocurrencies, commodities, currencies, indexes and web search results during and prior to the COVID-19 pandemic

Deni Memic*

Higher Colleges of Technology,
Business Division,
Academic City, Dubai, United Arab Emirates
Email: dmemic@hct.ac.ae
*Corresponding author

Selma Skaljic-Memic

Central Bank of Bosnia and Herzegovina,
Sarajevo, Bosnia and Herzegovina
Email: selma.skaljic@hotmail.com

M.N.S. Mohamed Noor Saif Almehairi

Higher Colleges of Technology,
Business Division Student,
Academic City, Dubai, United Arab Emirates
Email: H00350206@hct.ac.ae

Abstract: We observe the relationship and causality between cryptocurrencies on one, and commodities, currencies, equity indexes and web search results on the other side. We use prices of Bitcoin and Ethereum for cryptocurrencies, prices of crude oil and gold for commodities, Euro-US Dollar, Euro-Swiss Franc exchange rates for currencies, Dow Jones Industrial Average for market index and Google Trends® data as a measure of worldwide web search results for cryptocurrencies of interest. We find that Bitcoin and web search results correlation went from highly positive to low negative during the COVID-19 period. The results of the study show that the price of Bitcoin and Ethereum can be modelled using different combinations of commodities, currencies, indexes and web search results, with web search results and Dow Jones Industrial Average exhibiting best predictive power both concurrently and one day in advance. Our best performing models were able to explain more than 95% and 90% of Bitcoin and Ethereum price variability respectively. We also find strong evidence of web search traffic impacting both Bitcoin and Ethereum prices at all tested lags, as well as some evidence of gold impact on Bitcoin and EUR/CHF impact on Ethereum.

Keywords: cryptocurrencies; commodities; currencies; indexes; web search; COVID-19.

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Biographical notes: Deni Memic is an Academic Program Chair and Professor of Finance at Higher Colleges of Technology, Dubai, United Arab Emirates. He is a CFA charter holder and an experienced banker.

Selma Skaljic-Memic is ex-Expert Officer in the Department of Accounting and Finance at Central Bank of Bosnia and Herzegovina. She is a CFA Level 2 candidate and holds an MBA from Griffith College Dublin.

M.N.S. Mohamed Noor Saif Almehairi is a finance student at Higher Colleges of Technology Dubai, United Arab Emirates.

1 Introduction

Bitcoin was created in 2009 by Satoshi Nakamoto, with an aim of setting up a quick, cheap and an alternative way of making online payments to the traditional banking payment system, setting up foundations for many other cryptocurrencies that were setup later. As an investment opportunity, Bitcoin gained investors attention, providing substantial returns until reaching an all-time high price of more than USD 18,000 in April 2018. There are around 18 million Bitcoins in circulation with a market cap in Q1 2020 of 118 billion US dollars according to statistica.com. Some authors, though argue that it does not have fundamental value (Cheah and Fry, 2015).

Apart from gaining interest from investors, cryptocurrencies have been closely observed by academics too. Several studies have looked at the emerging asset from different perspectives. One of the studies (Colianni et al., 2015) targeted the possibility setting trading strategies for investments in the cryptocurrencies, observing number of times cryptocurrencies are mentioned on Twitter. The authors conducted the study through getting a python data set called Tweepy, which is an open-source data set that access to Twitter's API. They would use two different ways of comparing between the data set and the prices for every period, one of which is the text classification and the other one is the sentiment analysis program. The accuracy of the results reported was over 90%, for both hour-to-hour and day-to-day basis.

Another study (Katsiampa, 2019) looked at the volatility dynamics and interdependencies of Etherium and Bitcoin, and how their values are affected by the release of major news. The authors used a dataset of the closing prices of both cryptocurrencies from August 2015 to January 2018 and found that until the first quarter of 2017, and found that these cryptocurrencies are very reactive to major news. By using GARCH models, Dyhrberg (2016) studies the identity of the Bitcoin in relation to the Gold and the American Dollar, as well as the capability of the cryptocurrency to be used in portfolio management. The author reports that Bitcoin has more similarities with the currency than it has with the commodity.

Conlon and McGee (2020) reported their that Bitcoin fails to provide shelter for investors in turbulent periods like 2020 during the COVID-19 pandemic. On the other hand, Yarovaya et al. (2020) report that COVID-19 has not amplified herding in cryptocurrency markets. Contrary results were reported by Mnif et al. (2020) who investigated the efficiency level of five cryptocurrencies with highest market cap and detected the existence of herding behaviour markets using the generalised Hurst exponent as an evaluation measurement of fractality by means of the multi-fractal detrended fluctuation approach. They also showed that COVID-19 has a positive impact on the cryptocurrency market efficiency.

A group of authors (Bouri et al., 2017) studied the effectiveness of using the Bitcoin as a hedge against different commodities and indices. With a use of a bivariate DCC model, they find fount that Bitcoin is a weak hedge in the western markets, but a strong one in the Asian markets as well as that it can be a solid hedge against commodities.

Another group of authors (Valencia et al., 2019) looked at implementation of machine learning tools on social media information relating to the cryptocurrency. They reported to have used twenty million tweets relating to the subject, and applied different machine learning tools such as MLP, SVM, and RF, with Litecoin gaining the highest percentage of 0.8 precision score, followed by Bitcoin and Ripple then Ethereum, and the MLP was the best model providing the best results for three out of the four tested cryptocurrencies.

Vo et al. (2019) looked at ability of discerning Ethereum prices using the news and historical price data, while Misnik et al. (2019) used neural network to predict the market price of cryptocurrencies using psychological factors and social network factors.

A recent study by Alonso-Monslave et al. (2020) compared two different neural network architectures in providing an accurate prediction the value against the dollar in the next minute for six different cryptocurrencies, using 18 different technical indicators.

This research focuses on determining the relationship and possible causality between cryptocurrencies on one side, and commodities, currencies, equity indexes and web search results on the other side.

2 Methodology and data

We use prices of Bitcoin and Ehtereum for cryptocurrencies, Crude Oil WTI futures and Gold futures for commodities, Euro-US Dollar, Euro-Swiss Franc exchange rates for currencies, Dow Jones Industrial Average for equity index and Google Trends® data as a measure of worldwide web search results for cryptocurrencies of interest.

Table 1 List of variables used

Variable abb.	*Variable description*
(Ln) BITUSD	Bitcoin
(Ln) ETHUSD	Ethereum
(Ln) DJI	Dow Jones Industrial Average
(Ln) GC	Gold futures
(Ln) CL	Crude Oil WTI futures
(Ln) EURUSD	Euro US Dollar (EUR/USD)
(Ln) EURCHF	Euro Swiss Franc (EUR/CHF)
(Ln) WEBBIT	eb search results for Bitcoin (Google Trends)
(Ln) WEBETH	Web search results for Ethereum (Google Trends)

Source: Authors' work

High frequency (daily) market price data for Bitcoin is obtained for the period between 02/02/2012 and 15/04/2020. This data is matched with corresponding daily prices/values of Dow Jones Industrial Average, Euro-US Dollar, Euro-Swiss Franc exchange rates, Crude Oil WTI futures, Gold futures, Ehtereum and Google Trends. Bitcoin price dataset includes total of 2,050 observations. Starting date for Bitcoin price observations was chosen rather than the date of Bitcoin introduction as the price movements prior to 02/02/2012 were insignificant. Weekend and non-trading days are excluded for all variables. Financial used in the study are obtained from investing.com, while web search results are obtained from Google Trends. Ethereum dataset starts from 10/03/2016 as that is the earliest date when the daily price data becomes available in the used data source. Ethereum was introduced only few months before that date.

For modelling purposes, we will used natural logarithm transformation of variables.

Google Trends data are obtained as a relative number, where 100 represents a period where worldwide Google search traffic was the highest and 1 represents a period where Google search traffic was the lowest.

Using multiple regression analysis, number of different cryptocurrencies price models are constructed. Daily price of two major cryptocurrencies Bitcoin and Ehtereum are used as dependent variables whereas Crude Oil WTI futures, Gold futures Euro-US Dollar, Euro-Swiss Franc exchange rates, S&P500 and Google Trends® are used as independent variables or predictors.

$$Y = \alpha + \sum_{i=1}^{n} \beta_i X_i + \varepsilon$$

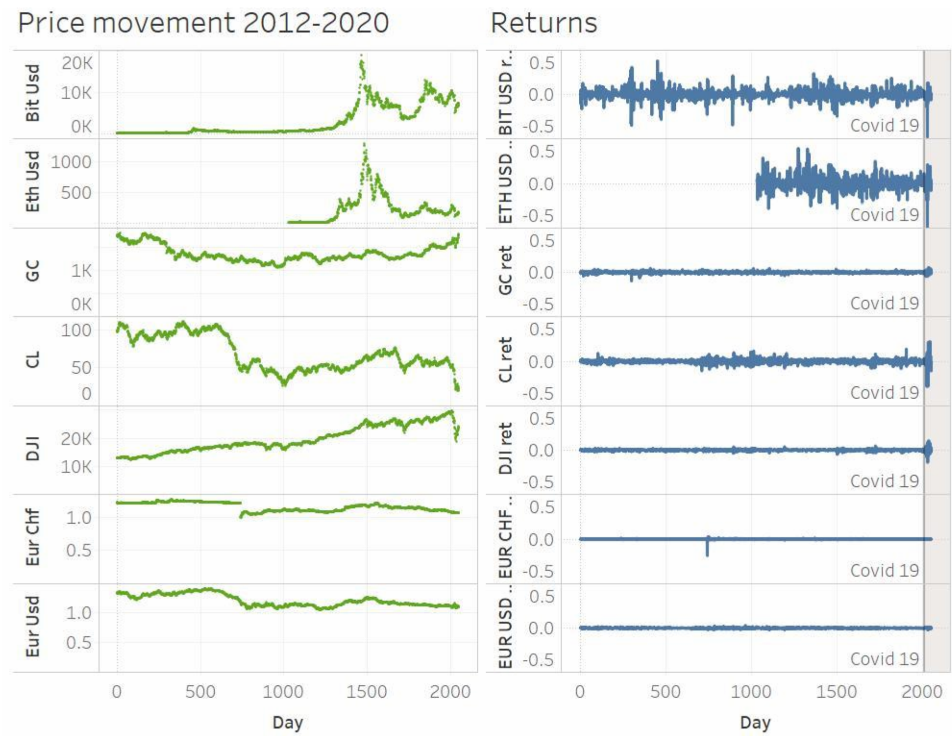
We utilise methodology developed by Granger (1969) called Granger causality test to assess the strength between variables with significant relationships. Granger causality is normally tested in the on-text of linear regression models. For illustration, consider a bivariate linear autoregressive model of two variables X_1 and X_2:

$$X_1(t) = \sum_{j=1}^{p} A_{11,j} X_1(t-j) + A_{12,j} X_2(t-j) + E_1(t)$$

$$X_2(t) = \sum_{j=1}^{p} A_{21,j} X_1(t-j) + A_{22,j} X_2(t-j) + E_2(t)$$

where p is the maximum number of lagged observations included in the model (the model order), the matrix A contains the coefficients of the model (i.e., the contributions of each lagged observation to the predicted values of $X_1(t)$ and $X_2(t)$, and E_1 and E_2 are residuals (prediction errors) for each time series. If the variance of E_1 or E_2 is reduced by the inclusion of the X_2 (or X_1) terms in the first (or second) equation, then it is said that X_2 (or X_1) Granger-(G)-causes X_1 (or X_2). In other words, X_2 G-causes X_1 if the coefficients in A_{12} are jointly significantly different from zero. This can be tested by performing an F-test of the null hypothesis that $A_{12} = 0$, given assumptions of covariance stationarity on X_1 and X_2. The magnitude of a G-causality interaction can be estimated by the logarithm of the corresponding F-statistic (Geweke, 1982). Note that model selection criteria, such as the Bayesian information criterion (Schwarz, 1978) or the Akaike information criterion (Akaike, 1974), can be used to determine the appropriate model order p.

Figure 1 Data overview (2012–2020) (see online version for colours)



2.1 *Relationship between cryptocurrencies and commodities, currencies, equity indexes and web search results*

We firstly examine the relationship between cryptocurrencies and commodities, currencies, equity indexes and web search results. Cryptocurrencies are different to other chosen assets, as they do not have fundamental value. First hypothesis is constructed as follows:

H1 There is a significant relationship between cryptocurrencies and commodities, currencies, equity indexes and web search results.

2.2 *Causality between cryptocurrencies and commodities, currencies, equity indexes and web search results*

Next, we examine if any of commodities, currencies, equity indexes and web search results cause the price of cryptocurrencies. Cryptocurrencies are different to other chosen assets, as they do not have fundamental value. Second hypothesis is constructed as follows:

H2 There is a causal relationship between commodities, currencies, equity indexes and web search results and cryptocurrencies.

Table 2 Descriptive statistics total sample

Variable	*BITUSD*	*ETHUSD*	*DJI*	*GC*	*CL*	*EURUSD*	*EURCHF*
Mean	2,792.30	232.18	19,496.48	1,347.86	67.69	1.20	1.15
Median	606.10	180.75	17,948.03	1,299.20	59.63	1.16	1.14
Mode	5.10	12.01	12,837.33	1,313.70	52.14	1.13	1.20
SD	3,704.43	233.08	4,655.16	168.19	22.60	0.10	0.06
Kurtosis	0.81	3.10	–1.11	-0.11	–1.20	–1.20	–1.40
Skewness	1.31	1.70	0.37	0.86	0.36	0.48	–0.02
Minimum	4.30	6.70	12.101.46	1,050.80	19.87	1.04	0.99
Maximum	18,934.00	1,283.70	29.551.42	1,794.10	110.53	1.39	1.26
Count	2,050	1,019	2,050	2,050	2,050	2,050	2,050

Source: Authors' work

Number of models using linear regression analysis are created with BITUSD and ETHUSD used as dependent and several combinations of other variables as independent variables. We have chosen data as of 21/02/2020 as a cut-off date for COVID-19 effects. This date was chosen as a cut-off as equities seem to have started reacting from that day onwards. Descriptive statistics are presented for separately for total sample price and returns movement, pre-COVID-19 and COVID-19 period as well as for the full sample in Tables 3 to 5.

Table 3 Descriptive statistics pre-COVID-19

Variable	*BITUSD*	*ETHUSD*	*DJI*	*GC*	*CL*	*EURUSD*	*EURCHF*
			Pre-COVID-19				
Mean	2,710.26	234.48	19,428.64	1,342.63	68.36	1.20	1.15
Median	595.00	181.65	17,902.51	1,296.50	60.07	1.16	1.14
Mode	5.10	12.01	12,837.33	1,313.70	52.14	1.13	1.20
SD	3,684.02	236.97	4,658.68	164.88	22.20	0.10	0.06
Kurtosis	1.03	2.86	–1.09	0.07	–1.28	–1.22	–1.38
Skewness	1.39	1.65	0.40	0.91	0.40	0.45	–0.04
Minimum	4.30	6.70	12,101.46	1,050.80	26.21	1.04	0.99
Maximum	18,934.00	1,283.70	29,551.42	1,794.10	110.53	1.39	1.26
Count	2,013	982	2,013	2,013	2,013	2,013	2,013
			COVID-19				
Mean	7,255.56	170.99	23,187.57	1,632.51	30.96	1.10	1.06
Median	6,848.70	156.75	23,185.62	1,648.20	26.08	1.10	1.06
Mode	-	-	-	1,648.90	-	1.09	1.06
SD	1,297.30	45.60	2,486.18	75.89	10.64	0.02	0.00
Kurtosis	–0.90	–1.11	–0.91	–0.07	–1.00	–0.34	–0.27
Skewness	0.18	0.54	0,19	–0.50	0.77	0.38	0.60
Minimum	4,927.00	109.53	18,591.93	1,480.60	19.87	1.07	1.05
Maximum	9,674.10	265.97	27,960.80	1,768.90	51.43	1.14	1.07
Count	37	37	37	37	37	37	37

Source: Authors' work

Table 4 Descriptive statistics returns total sample

Variable	*BITUSD ret*	*ETHUSD ret*	*DJI ret*	*GC ret*	*CL ret*	*EURUSD ret*	*EURCHF ret*
Mean	0.0034	0.0025	0.0003	0.0000	–0.0008	–0.0001	–0.0001
Median	0.0024	–0.0002	0.0005	0.0000	0.0004	–0.0001	–0.0001
Mode	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SD	0.0536	0.0726	0.0106	0.0099	0.0249	0.0051	0.0051
Kurtosis	10.5977	7.3738	31.8796	8.6513	23.1736	2.4086	861.9708
Skewness	–0.5949	–0.0699	–1.1004	–0.4602	–0.8043	0.0193	–23.4556
Minimum	–0.4809	–0.5799	–0.1384	–0.0982	–0.2822	–0.0242	–0.1850
Maximum	0.3805	0.3925	0.1076	0.0560	0.2205	0.0302	0.0275
Count	2050	1018	2050	2050	2050	2050	2050

Source: Authors' work

Table 5 Descriptive statistics returns

Variable	*BITUSD ret*	*ETHUSD ret*	*DJI ret*	*GC ret*	*CL ret*	*EURUSD ret*	*EURCHF ret*
				Pre-COVID-19			
Mean	0.0037	0.0032	0.0004	0.0000	–0.0003	–0.0001	–0.0001
Median	0.0024	–0.0007	0.0006	0.0000	0.0006	–0.0001	–0.0001
Mode	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SD	0.0525	0.0700	0.0080	0.0095	0.0210	0.0050	0.0051
Kurtosis	8.3200	4.2415	3.6025	8.9185	3.8475	2.4243	851.3216
Skewness	–0.2668	0.4730	–0.4056	–0.6431	0.1409	0.0662	–23.3448
Minimum	–0.3506	–0.2822	–0.0471	–0.0982	–0.1079	–0.0242	–0.1850
Maximum	0.3805	0.3925	0.0486	0.0460	0.1369	0.0302	0.0275
Count	2013	981	2013	2013	2013	2013	2013
				COVID-19			
Mean	–0.0103	–0.0149	–0.0057	0.0014	–0.0267	0.0002	–0.0002
Median	0.0031	0.0040	–0.0140	0.0004	–0.0302	0.0004	–0.0004
Mode							
SD	0.0952	0.1231	0.0529	0.0242	0.0998	0.0085	0.0020
Kurtosis	16.8526	12.2916	0.1901	0.2969	2.1656	0.3723	0.0692
Skewness	–3.4091	–2.6215	–0.1034	0.2199	–0.0264	–0.6092	0.0708
Minimum	–0.4809	–0.5799	–0.1384	–0.0475	–0.2822	–0.0233	–0.0046
Maximum	0.1326	0.2106	0.1076	0.0560	0.2205	0.0143	0.0040
Count	37	37	37	37	37	37	37

Source: Source: Authors' work

Table 6 Price correlation table total sample

Variable	*BITUSD*	*ETHUSD*	*DJI*	*GC*	*CL*	*EURUSD*	*EURCHF*	*WEBBIT*	*WEBETH*
BITUSD	1.000								
ETHUSD	0.709	1.000							
DJI	0.862	0.439	1.000						
GC	0.113	0.152	–0.149	1.000					
CL	–0.300	0.520	–0.508	0.416	1.000				
EURUSD	–0.315	0.778	–0.557	0.360	0.912	1.000			
EURCHF	–0.199	0.727	–0.450	0.364	0.871	0.923	1.000		
WEBBIT	0.757	0.680	0.542	–0.052	–0.221	–0.131	–0.043	1.000	
WEBETH	0.481	0.704	0.161	–0.071	0.133	0.532	0.456	0.817	1.000

Source: Authors' work

Table 7 Returns correlation table total sample

Variable	*BITUSD*	*ETHUSD*	*DJI*	*GC*	*CL*	*EURUSD*	*EURCHF*	*WEBBIT*	*WEBETH*
BITUSD	1.000								
ETHUSD	0.592	1.000							
DJI	0.091	0.184	1.000						
GC	0.056	0.057	0.012	1.000					
CL	0.018	0.059	0.323	0.108	1.000				
EURUSD	–0.001	0.015	–0.015	0.311	0.039	1.000			
EURCHF	–0.037	–0.025	0.098	–0.078	0.069	0.224	1.000		
WEBBIT	0.011	0.041	0.004	0.033	0.005	0.028	0.002	1.000	
WEBETH	–0.007	0.058	0.015	0.018	0.011	0.055	0.033	0.817	1.000

Source: Authors' work

Table 8 Returns correlation table total sample (Ln)

Variable	*LnBITUSD*	*LnETHUSD*	*LnDJI*	*LnGC*	*LnCL*	*LnEUR USD*	*LnEUR CHF*	*LnWEBBIT*	*LnWEBETH*
LnBITUSD	1.000								
LnETHUSD	0.917	1.000							
LnDJI	0.947	0.778	1.000						
LnGC	–0.342	0.368	–0.205	1.000					
LnCL	–0.472	0.462	–0.472	0.406	1.000				
LnEURUSD	–0.483	0.669	–0.579	0.373	0.869	1.000			
LnEURCHF	–0.402	0.669	–0.475	0.374	0.843	0.923	1.000		
LnWEBBIT	0.915	0.882	0.851	–0.200	–0.351	–0.319	–0.226	1.000	
LnWEBETH	0.652	0.837	0.435	0.099	0.230	0.653	0.580	0.873	1.000

Source: Authors' work

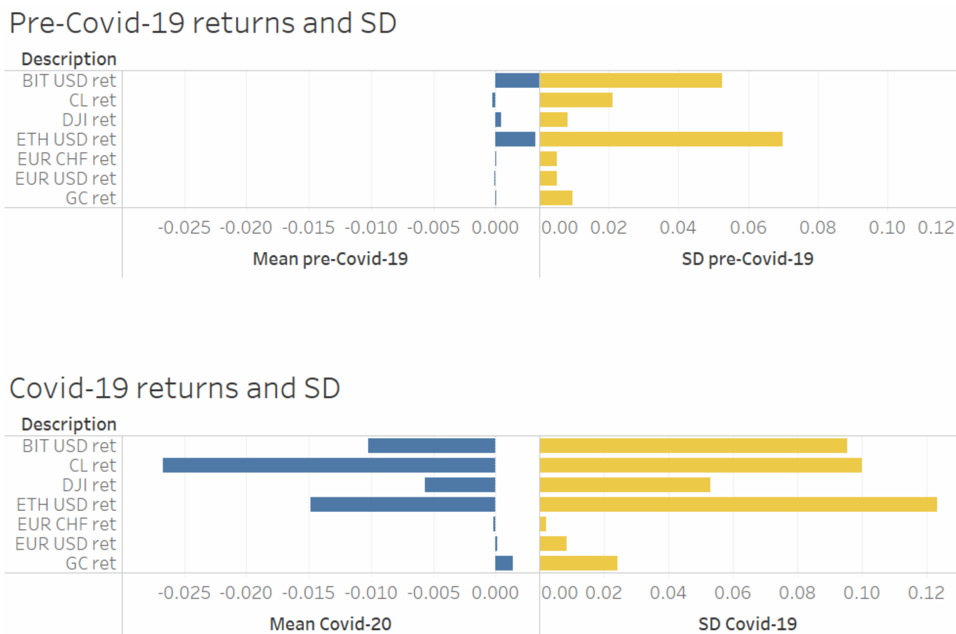
3 Results

It is observed that *BITUSD*, *DJI* and *GC* average prices during the COVID-19 period are above the historical average, with the highest dispersion observed for *BITUSD* and *GC*, indicating possibility that investors turned to Bitcoin and gold as safe haven during the crisis times (Table 3). Gold has long been considered as a defensive asset during the crisis periods. The Bitcoin finding was however unexpected and is studied further in this paper. It is also observed that all assets except for oil (CL) offered positive returns in pre-COVID-19 period, while most assets offered substantial negative returns in COVID-19 period, with high increase of volatility.

We observe price and return correlations between chosen variables and note that there is a high positive correlation between *BITUSD*, *ETHUSD*, *DIJ* and *WEBBIT*. *BITUSD* had negative correlation with *CL* and both observed currencies. As the dataset is split between pre-COVID-19 and COVID-19 period, we observe that there has been a substantial change in asset correlations between two periods. For some of the variables, the
COVID-19 effect was so significant driving the correlation went from –0.300 to +0.825. Interestingly, *BITUSD* and *WEBBIT* correlation went from +0.757 to –0.384 during the COVID-19 period (Figure 3). At the same time, there is a substantial increase in volatility of observed assets.

With variables transformed using natural logarithm, there is a high positive returns correlation between *LnBITUSD*, *LnETHUSD*, *LnDJI* and *LnWEBBIT*, all higher than 0.9.

Figure 2 Comparative overview of daily returns and SD pre-COVID-19 and during COVID-19 (see online version for colours)



Source: Authors' work

We construct several OLS models, with *LnBITUSD* and *LnETHUSD* as dependent variables and natural logarithm of other assets as independent variables. Set of models is constructed using concurrent data, and another set using one-day lag of independent variables. First set of models presented in Table 9 is created using *LnBITUSD* as dependent variable and natural logarithm of other variables from a concurrent period as dependent variables. First seven models are (1)–(7) use each variable individually and concurrently to predict the price of *BITUSD*. The R^2 for the models ranges between 0.117 for *LnGC* and 0.896 *LnDJI*. Each variable individually is highly significant, all at $p < 0.01$. In models (8)–(12), we test several variable combinations, to obtain optimal predictive result, considering multicollinearity. The R^2 for the models ranges between 0.897 (for a combination of *LnCL* and *LnDJI*) and 0.957 (for a combination of *LnGC*, *LnCL*, *LnEURUSD* and *LnDJI*). All variables are highly significant, all at $p < 0.01$.

Second set of models presented in Table 10, is constructed using one-day lagged independent variables to explore possible predictive power of data available a day in advance. This set of models also uses *LnBITUSD* as dependent variable with natural logarithm of other one-day lagged variables as dependent variables. First seven models are (1)–(7) use each variable individually to predict the price of BITUSD in the following day. The R^2 for the models ranges between 0.118 for *LnGC* and 0.896 *LnDJI*. Each variable individually is highly significant, all at $p < 0.01$. In models (8)–(12) we test several variable combinations, to obtain optimal predictive result. The R^2 for the models ranges between 0.902 (for a combination of *LnDJI* and *LnEURUSD*) and 0.956 (for a combination of *LnGC*, *LnCL*, *LnEURUSD* and *LnDJI*). All variables are highly significant, all at $p < 0.01$.

Table 9 *LnBITUSD* models with concurrent dependent variables

LnBITUSD	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
LnETHUSD	0.689***											
	(0.00939)											
LnGC		–6.271***						–2.835***		–3.690***		–3.195***
		(0.381)						(0.118)		(0.109)		(0.0923)
LnCL			–3.032***						–0.206***			–1.835***
			(0.125)						(0.0517)			(0.0608)
LnEURUSD				–12.97***						4.721***		11.32***
				(0.520)						(0.192)		(0.271)
LnEURCHF					–16.15***							
					(0.813)							
LnWEBBIT						1.906***					0.829***	
						(0.0185)					(0.0215)	
LnDJI							8.765***	8.472***	8.625***	9.326***	5.627***	9.446***
							(0.0659)	(0.0595)	(0.0745)	(0.0628)	(0.0957)	(0.0524)
Constant	4.891***	51.60***	19.06***	8.719***	8.619***	3.307***	–79.88***	–56.58***	–77.64***	–59.67***	–50.35***	–57.94***
	(0.0466)	(2.740)	(0.522)	(0.100)	(0.118)	(0.0363)	(0.649)	(1.125)	(0.857)	(0.996)	(0.912)	(0.831)
Observations	1,019	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050
R-squared	*0.841*	*0.117*	*0.223*	*0.233*	*0.162*	*0.838*	*0.896*	*0.919*	*0.897*	*0.938*	*0.940*	*0.957*

Notes: Standard error in brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Source: Authors' work

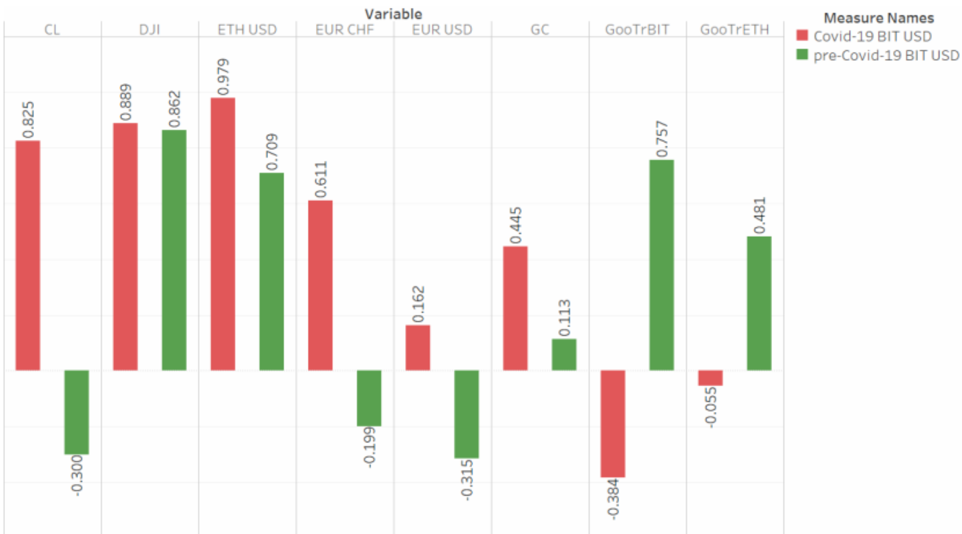
Table 10 *LnBITUSD* models with one-day lagged dependent variables

LnBITUSD	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
L1LnETHUSD	0.687***											
	(0.0094)											
L1LnDJI		8.755***						8.459***	9.284***	9.314***	5.600***	9.435***
		(0.066)						(0.0595)	(0.0785)	(0.0628)	(0.0955)	(0.0527)
L1LnGC			–6.302***					–2.847***		–3.708***		–3.193***
			(0.380)					(0.118)		(0.109)		(0.0931)
L1LnCL				–3.035***								–1.829***
				(0.125)								(0.0617)
L1LnEURUSD					–12.96***				2.647***	4.732***		11.29***
					(0.520)				(0.228)	(0.192)		(0.273)
L1LnEURCHF						–16.11***						
						(0.813)						
L1LnWEBBIT							1.905***				0.833***	
							(0.0184)				(0.0215)	
Constant	4.901***	–79.78***	51.82***	19.07***	8.718***	8.617***	3.311***	–56.37***	–85.45***	–59.42***	–50.08***	–57.86***
	(0.0467)	(0.651)	(2.739)	(0.523)	(0.100)	(0.118)	(0.0361)	(1.127)	(0.797)	(0.998)	(0.911)	(0.836)
Observations	1,018	2,049	2,049	2,049	2,049	2,049	2,049	2,049	2,049	2,049	2,049	2,049
R-squared	*0.840*	*0.896*	*0.118*	*0.223*	*0.233*	*0.161*	*0.839*	*0.919*	*0.902*	*0.937*	*0.940*	*0.956*

Notes: Standard error in brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Source: Authors' work

Figure 3 Comparative overview of asset correlations pre-COVID-19 and during COVID-19 (see online version for colours)



Source: Authors' work

Table 11 Granger causality test *LnBITUSD*

Causes		*Dependent*	*Lag 2*	*Lag4*	*Lag 6*	*Lag 8*	*Lag 10*
LnETHUSD	→	*LnBITUSD*	3.0212	4.0377	10.376	14.801**	15.664
LnDJI	→	*LnBITUSD*	2.8772	5.9893	5.2708	6.0838	18.044**
LnGC	→	*LnBITUSD*	1.3238	1.4462	10.009	10.658	30.069***
LnCL	→	*LnBITUSD*	0.00379	10.457**	9.125	6.2087	5.8949
LnEURUSD	→	*LnBITUSD*	7.1913**	8.5827*	8.4095	9.7455	15.891
LnEURCHF	→	*LnBITUSD*	4.9673*	4.0455	2.685	5.3763	8.6633
LnWEBBIT	→	*LnBITUSD*	17.379***	17.618***	28.421***	28.934***	34.642***
ALL	→	*LnBITUSD*	29.025***	44.624**	73.398***	87.021***	130.06***

Notes: The symbol → indicates direction of Granger causality. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Source: Authors' work

We also conduct a Granger causality test with *LnBITUSD* as a dependent and other assets as causing variables with 2, 4, 6, 8 and 10 lags, and present the results in Table 11. The causality effect is significant with *LnETHUSD* (lag 8, $p < 0.05$), *LnDJI* (lag 10, $p < 0.05$), *LnGC* (lag 10, $p < 0.01$), *LnCL* (lag 4, $p < 0.05$), *LnEURUSD* (lag 2, $p < 0.10$), and *LnWEBBIT* (all lags, $p < 0.01$). Collectively all dependent variables also have significant Chi2 in all lags.

Table 12 *LnETHUSD* models with concurrent dependent variables

LnETHUSD	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
LnBITUSD	1.221***											
	(0.0166)											
LnDJI		7.606***						7.940***	7.382***	6.232***	4.980***	8.095***
		(0.193)						(0.227)	(0.232)	(0.155)	(0.102)	(0.213)
LnGC			6.468***					–1.128***		0.217		–2.180***
			(0.513)					(0.408)		(0.269)		(0.321)
LnCL				3.356***					0.297*			–1.697***
				(0.202)					(0.172)			(0.141)
LnEURUSD					24.71***					18.35***		20.06***
					(0.861)					(0.497)		(0.487)
LnEURCHF						29.94***						
						(1.044)						
LnWEBETH							1.398***				1.029***	
							(0.0286)				(0.0174)	
Constant	–5.215***	–71.67***	–41.78***	–8.602***	1.659***	1.503***	1.461***	–66.91***	–70.61***	–61.72***	–47.72***	–56.67***
	(0.137)	(1.938)	(3.688)	(0.804)	(0.113)	(0.118)	(0.0718)	(2.587)	(2.031)	(1.697)	(1.009)	(1.643)
Observations	1,019	1,019	1,019	1,019	1,019	1,019	1,017	1,019	1,019	1,019	1,017	1,019
R-squared	*0.841*	*0.605*	*0.135*	*0.214*	*0.448*	*0.447*	*0.701*	*0.608*	*0.606*	*0.832*	*0.911*	*0.853*

Notes: Standard error in brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Source: Authors' work

Table 13 *LnETHUSD* models with one-day lagged dependent variables

LnETHUSD	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
L1LnBITUSD	1.217***											
	(0.0167)											
L1LnDJI		7.584***						7.936***	6.280***	6.241***	4.950***	8.106***
		(0.193)						(0.227)	(0.131)	(0.157)	(0.101)	(0.215)
L1LnGC			6.494***					–1.192***		0.127		–2.235***
			(0.515)					(0.411)		(0.273)		(0.325)
L1LnCL				3.451***								–1.710***
				(0.203)								(0.144)
L1LnEURUSD					24.67***				18.23***	18.26***		19.97***
					(0.862)				(0.497)	(0.502)		(0.492)
L1LnEURCHF						30.04***						
						(1.044)						
L1LnWEBETH							1.400***				1.033***	
							(0.0285)				(0.0173)	
Constant	–5.185***	–71.45***	–41.96***	–8.982***	1.664***	1.491***	1.459***	–66.41***	–60.63***	–61.15***	–47.42***	–56.31***
	(0.137)	(1.935)	(3.707)	(0.809)	(0.113)	(0.118)	(0.0714)	(2.596)	(1.304)	(1.716)	(1.001)	(1.660)
Observations	1,019	1,019	1,019	1,019	1,019	1,019	1,016	1,019	1,019	1,019	1,016	1,019
R-squared	*0.840*	*0.604*	*0.135*	*0.221*	*0.446*	*0.449*	*0.704*	*0.607*	*0.830*	*0.830*	*0.912*	*0.850*

Notes: Standard error in brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Source: Authors' work

Set of models are presented in Table 12 is created using *LnETHUSD* as dependent variable and natural logarithm of other variables from a concurrent period as dependent variables. First seven models are (1)–(7) use each variable individually and concurrently to predict the price of *ETHUS*D. The R^2 for the models ranges between 0.135 for *LnGC* and 0.841 *LnBITUSD*. Each variable individually is highly significant, all at $p < 0.01$. In models (8)–(12), we test several variable combinations, to obtain optimal predictive result, controlling for multicollinearity. The R^2 for the models ranges between 0.606 (for a combination of *LnCL* and *LnDJI*) and 0.911 (for a combination of *LnWEBETH* and *LnDJI*). Most of the variables are highly significant, all at $p < 0.01$.

Table 14 Granger causality test ETHUSD

Causes		*Dependent*	*Lag 2*	*Lag 4*	*Lag 6*	*Lag 8*	*Lag 10*
LnBITUSD	→	LnETHUSD	5.349*	11.859**	12.88**	15.307*	19.446**
LnDJI	→	LnETHUSD	0.74092	2.8034	3.0098	4.3373	14.503
LnGC	→	LnETHUSD	2.4206	2.2567	4.4872	8.498	20.143**
LnCL	→	LnETHUSD	0.18643	2.8246	3.4048	6.1622	7.0842
LnEURUSD	→	LnETHUSD	8.6043**	7.8805*	8.0561	28.851***	35.813***
LnEURCHF	→	LnETHUSD	9.2024**	9.6955**	10.996*	18.81**	22.949**
LnWEBETH	→	LnETHUSD	26.117***	25.195***	29.128***	31.274***	29.483***
ALL	→	LnETHUSD	41.603***	52.449***	63.256**	104.44***	136.82***

Notes: The symbol → indicates direction of Granger causality. $^{**}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Source: Authors' work

Another set of models presented in Table 13, is constructed using one-day lagged independent variables to explore possible predictive power of data available a day in advance. This set of models also uses *LnETHUSD* as dependent variable with natural logarithm of other one-day lagged variables as dependent variables. First seven models are (1)–(7) use each variable individually to predict the price of *ETHUSD* in the following day. The R^2 for the models ranges between 0.135 for *LnGC* and 0.840 *LnBITUSD*. Each variable individually is highly significant, all at $p < 0.01$. In models (8)–(12), we test several variable combinations, to obtain optimal predictive result. The R^2 for the models ranges between 0.607 (for a combination of *LnDJI* and *LnGC*) and 0.912 (for a combination of *LnWEBETH* and *LnDJI*). Most of the variables are highly significant, all at $p < 0.01$.

Granger causality test with *LnETHUSD* as a dependent and other assets as causing variables with 2, 4, 6, 8 and 10 lags, are presented in Table 14. The causality effect is significant with *LnBITUSD* (all lags, $p < 0.05$ and $p < 0.01$), *LnGC* (lag 10, $p < 0.05$), *LnEURUSD* (lags 2, 4, 8 and 10, with 8 and 10 lags at $p < 0.01$), *LnEURCHF* (all lags), and *LnWEBETH* (all lags, p <0 .01). Collectively, all dependent variables also have significant Chi2 in all lags.

4 Findings and discussion

We used high frequency data for prices of cryptocurrencies represented by Bitcoin and Ehtereum, commodities represented by Crude Oil WTI futures and Gold futures, currencies represented by EuroUS Dollar, Euro-Swiss Franc exchange rates, equity index represented by Dow Jones Industrial Average for and Google Trends® data as a measure of worldwide web search results for cryptocurrencies of interest. Our goal was to observe the relationship and causality between cryptocurrencies on one, and commodities, currencies, equity indexes and web search results on the other side.

Data for Bitcoin was obtained for the period between 02/02/2012 and 15/04/2020, with total of 2050 daily data points. This data was matched with corresponding daily prices/values of Dow Jones Industrial Average, Euro-US Dollar, Euro-Swiss Franc exchange rates, Crude Oil WTI futures, Gold futures, Ehtereum and Google Trends. Ethereum dataset starts from 10/03/2016.

It was observed that Bitcoin, Dow Jones Industrial Average and gold average prices during the COVID-19 period are above the historical average, with the highest dispersion observed for Bitcoin and gold, indicating possibility that investors turned to Bitcoin and gold as safe haven during the crisis times, confirming gold as a defensive asset during the crisis periods. Bitcoin finding was somewhat surprising, as one would expect investors would turn to less risky assets during the crisis of this magnitude. It is also observed that all assets except for crude oil offered positive returns in pre-Covid19 period, while most assets offered substantial negative returns in COVID-19 period, with substantial increase of volatility. We have also a high positive correlation between Bitcoin, Ethereum, Dow Jones Industrial Average and web search results. Bitcoin had negative correlation with crude oil and both observed currencies.

We find a substantial change in asset correlations between pre-COVID-19 and COVID-19 period, Bitcoin price and web search results had a high correlation of +0.757 in the pre-COVID-19 but the correlation turned negative –0.384 during the COVID-19 period.

We used OLS models to test if significant relationship exists between cryptocurrencies and commodities, currencies, equity indexes and web search results. Our models show a significant relationship between Bitcoin, Crude Oil WTI futures, Gold futures, Euro-US Dollar, Euro-Swiss Franc exchange rates, Dow Jones Industrial Average for and Google Trends data. Best performing model including a combination of gold, crude oil, Euro and Dow Jones, was able to explain almost 96% of Bitcoin price variability in the observed period. Gold and crude oil price increase was associated with concurrent decrease of Bitcoin price, while Dollar (to Euro) and Dow Jones Industrial Average increase was associated with a concurrent increase of Bitcoin price.

We used OLS models to test if significant relationship exists between cryptocurrencies and commodities, currencies, equity indexes and web search results. Our models show a significant relationship between Bitcoin, Crude Oil WTI futures, Gold futures, Euro-US Dollar, Euro-Swiss Franc exchange rates, Dow Jones Industrial Average for and Google Trends data. Best performing model including a combination of gold, crude oil, Euro and Dow Jones, was able to explain almost 96% of Bitcoin price variability in the observed period. Gold and crude oil price increase was associated with concurrent decrease of Bitcoin price, while Dollar (to Euro) and Dow Jones Industrial Average increase was associated with a concurrent increase of Bitcoin price. Significant predictive power was also achieved using a combination of Dow Jones and Bitcoin web search results where a higher Dow Jones and more web searches for Bitcoin are associated with a higher Bitcoin price.

In the next step, we constructed a set of models using one-day lagged independent variables to explore possible predictive power of data available a day in advance. Our models show a significant relationship between Bitcoin, one-day lagged values of Crude Oil WTI futures, Gold futures, EuroUS Dollar, Euro-Swiss Franc exchange rates, Dow Jones Industrial Average for and Google Trends data. Best performing model including a combination of previous day gold, crude oil, Euro and Dow Jones values, were able to explain almost 96% of Bitcoin price variability the next day. Gold and crude oil price increase was associated with concurrent decrease of Bitcoin price, while Dollar (to Euro) and Dow Jones Industrial Average increase was associated with a concurrent increase of Bitcoin price. Significant predictive power was also achieved using a combination of previous day Dow Jones and Bitcoin web search results where a higher Dow Jones and more web searches for Bitcoin are associated with a higher subsequent Bitcoin price.

Our results show strong evidence of web search results impacting both Bitcoin and Ethereum prices at all tested lags (2, 4, 6, 8 and 10 all at $p < 0.01$). This indicates that web remains the main source on gathering information about a crypto investment. More search results, leads to more demand and consequently increase in crypto prices. There is also some evidence of sporadic impact of other tested variables at different significance levels and lags as presented in Tables 11 and 14. Most significant impact on Bitcoin price was gold with a 10 days lag, and Ethereum impacted by Bitcoin and EUR/CHF. We also find that collectively all studied variables impact the prices Bitcoin and Ethereum at all tested lags.

5 Recommendations

Results of this study can be used, along with other available tools, to construct future short-term market expectations for cryptocurrencies. The results can be used to enhance existing portfolio construction models in a way to include novel variables that proved to have significant predictive ability and impact on cryptocurrency price movement. The results can also be used as a starting point for further complementary academic research in the filed.

This study is limited to a number of variables used to explain the variability of Bitcoin and Ethereum price movements. As a novel investment opportunity, and a difficult to predict future, other variables could also be studied against such assets to gather more insight as to the key drivers of the market movements.

Conventional asset classes such as equities, fixed income, alternatives have been studied extensively in the past and used efficiently to construct investors' portfolios. Recent FinTech solutions and innovations such as cryptocurrencies are an emerging area of interest to academics and practitioners.

Cryptocurrencies can be used as a new asset class to improve portfolio performance and add to the diversification benefits, together with asset classes that it has low or negative correlation with. Even though results of this study have limited reach into the crisis period, due to the fact the paper is authored in the midst of the COVID-19 crisis and used dataset includes 37 days of bear market, caused by the COVID-19 pandemic, the results indicate that apart from gold, Bitcon offered above average return during the period when all other studies assets had highly negative returns. These results are to be used with caution, due to the short time span of data used in this study.

It is recommended that, as more data becomes available, possible micro and macro-economic effects of such and similar FinTech innovations are studied in more depth.

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