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Exploring the relationship between cryptocurrencies and hedge funds during COVID-19 crisis

Soumaya Ben Khelifa a, b, Khaled Guesmi b, Christian Urom b

a University Tunis Carthage, Tunis, Tunisia
b Center of Research for Energy and Climate Change (CRECC), Paris School of Business, Paris, France

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ABSTRACT

In this paper, we investigated the relationship between cryptocurrency market and hedge funds in two different ways. First, we focus on the dependence between Cryptocurrency hedge funds and conventional hedge funds strategies using VAR and VECM models, while analyzing the impact of COVID-19 on the hedge funds’ values. Secondly, we choose between ARDL and ARDL-ECM models to study the effects of cryptocurrency price changes on Crypto-Currency hedge funds’ values during COVID-19 crisis. Our empirical findings demonstrate that there is substantial interactions between Crypto-Currency and conventional hedge funds. The COVID-19 pandemic has significant negative impact on the performance of the following hedge funds: Event Driven, Relative Value and Distressed Debt fund strategies, this has reflected in a significant drop in their values during this critical period. However, we demonstrate that COVID-19 pandemic did not affect the relationship between crypto-currency hedge funds and both bitcoin and Ethereum. These findings hold profound implications for hedge funds managers, cryptocurrency market main players and policy makers. Our study is crucial in forecasting the performance of these markets especially during global pandemics.

1. Introduction

The global health crisis created by the COVID-19 pandemic has presented one of the worst challenges facing the global economy since the second World War. Many sectors and industries including the oil and gas sectors have been adversely affected by this crisis. Specifically, the large scale closure of industrial activities and the restrictions to travel due to the lockdown measures led to an unprecedented drop in the global demand for crude oil, leading to a sharp drop in prices with strong downward variations and has heightened the level of financial market risk (Albulescu, 2020; Mzoughi, Urom, Uddin, & Guesmi, 2020; Urom, Mzoughi, Abid, & Brahim, 2021, Urom, Ndubuisi, & Ozor, 2021). Following this, the COVID-19 pandemic and the concomitant economic, social and market turmoil is noted to have led to a dramatic fall in the market return of most financial assets during which time investors were attempting to broadly quantify the severity of the pandemic and its impact on the global economy and financial markets.

The economic and financial costs of the COVID-19 pandemic is believed to also have great implications for hedge funds managers, cryptocurrency markets participants as well as individual investors. Whereas the investment strategies of hedge funds have developed over the past decades, over the past recent years, cryptocurrencies markets have undergone remarkable development, leading to a frenzy of investment activities and interests from traditional investors (see e.g., Mokhtarian & Lindgren, 2018). As noted in Urom, Abid, Guesmi, and Chevallier (2020), given their numerous advantage including the lack of bank intermediation for settlement of transactions; low transaction fees; and a high degree of anonymity, the acceptance of digital currencies by businesses and organizations as a medium of exchange has increased in recent years. This is believed to have contributed to a considerable increase in consumer base, transaction frequency, and the attention of the general public, policymakers and investors. Corbet, Lucey, and Yarovaya (2018) argue that the increase in investors’ attention in the cryptocurrency markets has led to an increase in its consideration as a new category of investment assets.

Consequently, a growing literature has emerged with the aim of exploring the interactions between cryptocurrency as investment assets and other financial assets including equities, foreign exchange as well as commodities. Even more, Urom et al. (2020) argue that recent developments including the launch of Bitcoin futures and the increasing participation of institutional investors have also facilitated the increasing stream of research that aims to explore why and how digital
currencies may offer new opportunities with regards to the analysis of risk management and portfolio diversification strategies. Similarly, Charfeddine, Benlagha, and Maouchi (2020) document that cryptocurrencies are gradually establishing themselves as a new class of assets with unique features that make them significantly suitable for financial diversification. Hence, most financial analysis of the risk management opportunities of cryptocurrencies has mainly focused on their liquidity, correlation with other financial assets, investor sentiment and, ultimately, their potential to hedge the downside risk of other financial assets (see e.g. Bouri, Molinar, Azzi, Roubaud, & Hagfors, 2017; Baur, Hong, & Lee, 2018; Erdas & Caglar, 2018; Conrad, Custovic, & Ghysels, 2018; Guesmi, Saadi, Abid, & Fititi, 2019; Kang, McVayer, & Hernandez, 2019; Chan, Lc, & Wu, 2019; López-Cabarcos, Pérez-Pico, PINEIRO-CHOUZA, & SEVIĆ, 2019; KRISTJANPOLLER, BOURI, & TAKAISHI, 2020; SHAHZAD, BOURI, ROUBAUD, & KRISTOFEK, 2020; BOURI, LUCEY, & ROUBAUD, 2020; ZHANG, BOURI, GUPTA, & MA, 2021).

Perhaps, another recent crucial development in the cryptocurrency market space is the emergence of funds that specialize in the cryptocurrency markets. Given the potential of cryptocurrencies to offer significant returns compared to yields from traditional asset classes, a new wave of investment funds namely cryptocurrency hedge funds, has emerged which aims to provide active investment management in the cryptocurrency market space. In particular, Bianchi and Babiak (2020) argue that a large part of the market capitalization for all cryptocurrencies emerged from individual traders who trade on private exchanges of digital assets but, that the magnitude of higher returns (and volatility) from cryptocurrencies over those of traditional assets, has led to the establishment of the cryptocurrency hedge funds to offer active investment management.

Beyond the potential for higher returns, cryptocurrency hedge funds possesses some comparative advantage over traditional hedge funds. Specifically, cryptocurrencies are recent and largely unregulated asset class which creates an investment landscape with a variety of arbitrage opportunities and risk taking opportunities (BIANCHI & BABIAK, 2020; MAKAROV & SCHOAR, 2020). Secondly, in contrast to investments in traditional hedge funds, competition with the cryptocurrency hedge fund strategies are still mainly very limited. As documented in Bianchi and Babiak (2020), this limited level of competition especially from cheaper investment vehicles including Exchange Traded Funds (ETFs) is believed to put less pressure on funds managers to cut costs, increase leverage and to take extra risks. Lastly, the highly fragmented and multi-platform structure of the cryptocurrency markets have lent credence to the conjecture that they possess the potential of being separated from other traditional asset classes.

The above distinguishing contexts presented by the cryptocurrency hedge funds has elicited the interest of researchers regarding the performance of cryptocurrency funds as well as their return volatility and interdependencies with other hedge funds. For instance, Kapil and Gupta (2019) argue that the performance of cryptocurrency hedge funds appear not to have been very encouraging in the past recent years due to reasons such as high volatility and downward trends in cryptocurrencies caused by increased global financial market risks, which has led to the closure of many hedge funds. However, Bianchi and Babiak (2020) examined the aggregate performance of cryptocurrency hedge funds above those of alternative passive investment strategies and document some evidence of superior cryptocurrency hedge funds performance. However, to our best knowledge, no previous study has focused on the relationships between cryptocurrency hedge funds and other conventional hedge fund indices.

Moreover, the recent unprecedented situation created by the COVID-19 pandemic has demonstrated that a global health crisis has the potential to slowdown the global economy and increase the level of financial markets volatility. A growing literature has empirically demonstrated that global financial markets have been detrimentally affected by the COVID-19 pandemic and that the global financial markets have swiftly responded to the spread of the virus, with tremendous contagion effects across different asset classes and sectors of the economy (see e.g., Albulescu, 2020; Mzoughi et al., 2020; Zhang, Hu, & Ji, 2020; Goodell, 2020; Alawadhi, Al-Saiﬁ, Al-Awadhi, & Alhammadi, 2020; Cepoi, 2020; Sharif, Aloui, & Yaroyava, 2020; Urom, Mzoughi et al., 2021; Urom, Ndubusi, & Ozor, 2021). Specifically, using a global stock market representative index, Zhang et al. (2020) demonstrate that the risk levels of all the countries have increased significantly from 0.0071 in February 2020 to 0.0196 in March 2020. Consistent with the above, Ali, Alam, and Rizvi (2020) show that major global stock markets have experienced a decline up to double figures, with the S&P 500 displaying a 30% decline in value within 16 trading days. Further, Alawadhi et al. (2020) found evidence of significant negative impact of COVID-19 on stock returns across all companies included in the Hang Seng Index and Shanghai Stock Exchange Composite Index. Sharif et al. (2020) identified a short-term causality between COVID-19 pandemic and the US stock market. Even more, Akhtaruzzaman, Boubaker, and Sensoy (2020) document an significant increase in conditional correlations among the stock returns of firms across China and G7 countries following the COVID-19 pandemic.

An increasing empirical studies have also emerged with the aim of exploring the response of the cryptocurrency markets to the COVID-19 pandemic as well as changes in the interactions between cryptocurrencies and other traditional asset classes (see e.g. Lahmiri & Bekiros, 2020; Conlon & McGee, 2020; Mnif, Jarboui, & Mouakhar, 2020; Corbet, Larkin, & Lucey, 2020; Ali, Alam, and Rizvi, 2020; Goodell & Goutte, 2021; Ji, Zhang, & Zhao, 2020c). However, these studies document varying evidence on the influence of the cryptocurrency market to the evolution of the global health crisis as well as the interdependencies between the cryptocurrency market and conventional asset classes during this period. The divergence results are not unexpected given that these studies have adopted different econometric approaches and have focused on different financial assets, markets and regions.

In particular, Corbet et al. (2020) focused on the impact of COVID-19 pandemic on the safe haven potentials of cryptocurrencies and document some evidence that these assets are not safe haven neither have they acted as hedges during COVID-19 pandemic. Contrarily, they show evidence that these assets have acted as amplifiers of contagion effect during this period. Parallel to this, Ji et al. (2020) demonstrate that the safe haven roles of most financial assets including cryptocurrencies has been less effective while Goodell and Goutte (2021) show evidence that the levels of COVID-19 pandemic generated a rise in the price of cryptocurrencies. Even more, Lahmiri and Bekiros (2020) suggest that the cryptocurrencies market have been relatively more volatile than international stock markets during COVID-19 pandemic. However, to our best knowledge, none of the previous studies have focused on the interdependencies between the cryptocurrencies market and hedge fund strategies during the COVID-19 pandemic.

Consequently, this paper focuses on the effects of COVID-19 pandemic on the interactions among cryptocurrencies, cryptocurrency hedge fund and traditional hedge fund strategies. Following this, this study makes the following important contributions to the literature on financial markets dynamics under the pandemic. First, we investigate the relationship between aggregate cryptocurrency hedge fund and different conventional hedge funds strategies using both the Vector Autoregressive (VAR) and Vector Error Correction models (VECM), while accounting for the impact of COVID-19 pandemic on hedge funds’ values. Secondly, we rely on the Autoregressive Distributed Lags (ARDL) and ARDL-VECM models to detect the effects of the mostly traded three cryptocurrencies on cryptocurrency hedge funds’ values during the COVID-19 pandemic. The chosen three cryptocurrencies represent over 80% of the 10 highest cryptocurrencies by market capitalization as at May 13, 2020 including Bitcoin, Ethereum and Tether.

The rest of this manuscript is structured as follows: Section 2 presents the modelling framework adopted for this study and the description of the dataset. We present and discuss our empirical results in Section 3 while Section 4 contains the conclusion and practical policy
implications.

2. Econometric framework

2.1. Cryptocurrency hedge funds and conventional hedge funds strategies

We analyse the bivariate relationship between the Cryptocurrency Hedge Fund Index and selected hedge fund indices. To do this, this study relies on granger causality tests. First, we examine the presence of unit root problem by checking for the stationarity of all the time series. We use the most widely used unit root test namely the Augmented Dickey Fuller (ADF) test defined as follows:

\[
\Delta v_t = \alpha_t + \beta \sum_{i=1}^{p} \Delta v_{t-i} + \epsilon_t
\]  

(1)

Where \( v \) is the vector of the two variables; \( \alpha_t \) is the vector of intercepts; \( \beta \) is the vector of regression coefficients; \( p \) is the number of lags considered while \( \epsilon_t \) is the vector of error terms. We then proceed with the choice of the appropriate lag length using the Akaike information criterion (AIC) defined as AIC = 2k – 2 ln (L).Where \( k \) is the number of parameters while \( L \) is the maximum value of the likelihood of the model.

Next, we perform cointegration test using Johansen’s methodology to verify the presence of cointegration between the cryptocurrency market index and each hedge fund index. Thus, we create the following bivariate VAR models:

\[
CRTH_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i CRTH_{t-i} + \sum_{i=1}^{p} \beta_i HFI_{t-i} + COVID_t + u_t
\]  

(2)

\[
HFI_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i HFI_{t-i} + \sum_{i=1}^{p} \beta_i CRTH_{t-i} + COVID_t + u_t
\]  

(3)

Where \( CRTH_{t-i} \) is the Crypto-Currency Hedge Fund index value at month \( t \) while \( HFI_{t-i} \) is the conventional hedge fund index value. \( COVID \) is a dummy variable that has a value of 1 during the crisis period (December 2019 – April 2020). \( p \) is the number of lags according to AIC.

Finally, we apply the granger causality test using Wald test. We test the null hypothesis that the hedge fund index does not Granger-cause the Cryptocurrency Hedge Fund Index, defined as:

\[
H_0 = \sum_{p} \beta_i = 0; H_1 = \sum_{p} \beta_i \neq 0
\]

Similarly, we verify that the Cryptocurrency Hedge Fund Index does not Granger-cause the hedge fund index, defined as:

\[
H_0 = \sum_{p} \beta_i = 0; H_1 = \sum_{p} \beta_i \neq 0
\]

The Wald test statistics is based on \( \chi^2 \) distribution under the null hypothesis. The latter is rejected for values of the statistic that is statistically significance at the conventional levels, which supports the presence of Granger causality between the two time series.

However, if the variables are cointegrated, we employ the VEC model which is specified as follow:

\[
\Delta CRTH_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta CRTH_{t-1} + \sum_{i=1}^{p} \beta_i \Delta HFI_{t-1} + w_1 ECT_{t-1} + COVID_t + u_t
\]  

(4)

\[
\Delta HFI_t = \alpha_0 + \sum_{i=1}^{d} \gamma_i \Delta HFI_{t-1} + \sum_{i=1}^{d} \delta_i \Delta CRTH_{t-1} + w_2 ECT_{t-1} + COVID_t + u_t
\]  

(5)

Where \( \Delta \) is the first difference operator; \( p - 1 \) denotes that the lag length is reduced by 1. \( a; b; c; \) and \( d \) are the short-run dynamic coefficients which specifies short-term relationships among the variables while \( w_1 \) and \( w_2 \) are the speed of parameter adjustment to long term equilibrium. Lastly, \( u_t \) and \( u_t \) are the residuals terms.

2.2. The impact of the COVID-19 pandemic

In this section, we explore the relationship between cryptocurrency hedge funds and mainly traded cryptocurrencies. To do this, we rely on ARDL models to analyse the dynamic relationship between cryptocurrency hedge funds and the three largest cryptocurrencies by market capitalisation including Bitcoin, Ethereum and Tether during the COVID-19 Crisit. The ARDL econometric technique has been applied in several previous studies due to a number of proven advantages over other techniques such as the Johansen cointegration techniques. For instance, as noted in Ghatak and Siddiki (2001) the ARDL technique is a more statistically suitable approach to determining the validity of the cointegration relationship in small samples.

Secondly, while other cointegration approaches require all the regressors to be integrated of the same order, the ARDL technique can be applied whether the regressors are integrated of the same order or mixture of orders of integration (i.e. I(1) and/or I(0)). Hence, Pesaran, Shin, and Smith (2001) argue that the ARDL technique circumvents the pre-testing issues that are associated with standard cointegration, which requires that the variables be already classified into I(1) or I(0). Lastly, Pahlavani, Wilson, and Worthington (2005) argue that another crucial advantage of ARDL technique relates to its ability to avoid the difficulty in making a large number of choices including the treatment of deterministic elements and the order of VAR and the optimal number of lags to be used. This is because the estimation procedure of the ARDL approach permits the use of different optimal numbers of lags for different variables in the model.

Given the above rationales of the ARDL technique, first, we perform the ARDL bounds test for cointegration to study whether there is long-term causal relationships between cryptocurrency hedge funds and the three cryptocurrencies during the COVID-19 pandemic based on Pesaran and Smith (1995) and Pesaran et al. (2001) ARDL approach. The ARDL model for this study may be defined as follows:

\[
\Delta CRTH_t = \beta_0 + \sum_{p} \beta_1 \Delta CRTH_{t-1} + \sum_{p} \beta_2 \Delta BTC_{t-1} + \sum_{p} \beta_3 \Delta ETH_{t-1}
\]

\[
+ \sum_{p} \beta_4 \Delta TET_{t-1} + \sum_{p} \beta_5 \Delta (BTC^* COVID)_{t-1}
\]

\[
+ \sum_{p} \beta_6 \Delta (ETH^* COVID)_{t-1} + \sum_{p} \beta_7 \Delta (TET COVID)_{t-1} + \alpha_1 CO\ldots
\]

\[
+ \alpha_2 CRTH_{t-1} + \alpha_3 BTC_{t-1} + \alpha_4 ETH_{t-1} + \alpha_5 TET_{t-1}
\]

\[
+ \alpha_6 (BTC^* COVID)_{t-1} + \alpha_7 (ETH^* COVID)_{t-1} + \alpha_8 (TET^* COVID)_{t-1} + \epsilon_t
\]

where \( \beta_2 \) to \( \beta_8 \) denote short-term dynamic relationships; \( \alpha_2 \) to \( \alpha_8 \) represent the long-run dynamic relationships. \( p_1 \) to \( p_7 \) are the maximum lag orders determined by AIC or SCBE.

Hypotheses. The long-term equilibrium relationship between variables can be examined using F-statistics. \( H_0 \) and \( H_1 \) below denote the null hypothesis of no cointegration relationship and the alternative, indicating that there is cointegration relationship.

\[
H_0 = \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = \alpha_8 = 0
\]

\[
H_1 = \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = \alpha_8 \neq 0
\]

Following this, if there is no cointegration, we proceed to estimate the ARDL model which is reveals the long and short-term relationships between the variables. The ARDL model is specified as:
\[ \Delta \text{CRTH}_t = \beta_0 + \sum_{i=1}^{p_4} \beta_{1i} \Delta \text{CRTH}_{t-i} + \sum_{i=1}^{p_4} \beta_{2i} \Delta \text{BTC}_{t-i} + \sum_{i=1}^{p_6} \beta_{3i} \Delta \text{ETH}_{t-i} + \sum_{i=1}^{p_5} \beta_{4i} \Delta \text{TET}_{t-i} + \sum_{i=1}^{p_7} \beta_{5i} \Delta \text{COVID}_{t-i} + \sum_{i=1}^{p_8} \beta_{6i} \Delta (\text{BTC}^* \cdot \text{COVID})_{t-i} + \sum_{i=1}^{p_9} \beta_{7i} \Delta (\text{ETH}^* \cdot \text{COVID})_{t-i} + \sum_{i=1}^{p_5} \beta_{8i} \Delta (\text{TET}^* \cdot \text{COVID})_{t-i} + \gamma \text{ECT}_{t-i} + \epsilon_t \]

where \( \gamma \) denotes the speed of adjustment parameter while \( \text{ECT} \) is the error correction term. \( \beta_1 \) to \( \beta_8 \) represent short-term dynamic coefficients of the model’s adjustment to long-run equilibrium.

### 2.3. Data

The dataset for this study include cryptocurrency hedge funds index, the global hedge fund and the eight hedge fund strategies proposed in the Eurekahedge Hedge Fund index database. Particularly, we use the cryptocurrency Hedge Fund index (CRTH), and nine conventional hedge funds indices related to different strategies including Global Hedge fund index, Arbitrage index, Distressed Debt index, Even Driven index, Fixed Income index, Long Short Equities index, Macro index, Multi-Strategy index and Relative Value. This data cover the period from January 2014 to April 2020. The description of basic statistics for this all the time series expressed in natural logarithm is presented in Table 1. Results show that cryptocurrency hedge fund index has the highest mean value while the arbitrage index has the least of about 7.83 and 5.81 respectively. The cryptocurrency hedge fund index is also the most volatile as shown by the standard deviation whereas the macro index is the least volatile.

Further, following most previous studies, the data on cryptocurrencies is extracted from a cryptoasset database coinmarket. We focus on the top three most traded cryptocurrencies assets with the highest market capitalisation. This includes Bitcoin, Ethereum and Tether. The combined market capitalisation of the selected cryptocurrencies represents more than 80% of the top 10 cryptocurrencies by market capitalisation value as at end of 13 May 2020. The study period for this part of our analysis is from August 2015 to April 2020, totalling 57 monthly observations on closing prices and market capitalisation. Table 1 also presents basic statistics for the three cryptocurrencies. We observe that Bitcoin has highest value compared to Ethereum, Tether and all hedge funds indices and lower volatility than Crypto-Currency Hedge Fund and Ethereum.

### 3. Empirical results

Our empirical analysis begins with preliminary tests to confirm the presence of nonlinearities and the stationarity properties in the variables used for this study. Following this, we examined the presence of nonlinearities in all the variables using the Brock-Dechert-Scheinkman test for non-linearity proposed by Brock et al. (1987). As may be seen in Table 2, the BDS statistic is statistically significant for all the variables. This indicates the presence of non-linearities in all the time series used in this study. Having confirmed this, we rely on the ADF tests with structural break to examine the presence of unit roots in all the series as well as to detect possible break points for each variable. This is very crucial given that Granger, Huangb, and Yang (2000) argue that, the ADF test may offer erroneous results when the sample period includes some major events such as the great financial crisis and oil shocks. In this study, our sample covers periods of notable events in the evolution in the market for cryptocurrencies as well as the COVID-19 pandemic.

As shown in Table 2, results show that all the variables become stationary at their first difference and exhibit break points with the value of the statistic being greater than the test critical values across all the conventional levels of significance. This indicates that the cryptocurrency hedge fund index and all chosen conventional hedge funds indices, exhibit no unit roots and are stationary after first difference. Put differently, all variables appear to be integrated at order 1 (i.e. I(1)). Concerning the break points, all the hedge fund indexess witnessed a structural break during the period of the recent COVID-19 pandemic. Global hedge fund index, Arbitrage, Event Driven, Multi-Strategy and Relative value exhibited structural breaks in January 2020, Distressed Debt, Fixed income and Macro exhibited in February 2020 while Long Short Equities has its break point in December 2019. These findings corroborate our chosen crisis period which covers from December 2019 to April 2020.

In Table 3, we present the optimal lag length selection criteria test results. As may be seen, we rely on four different tests for the selection of optimal lag lengths for each VAR model including FPE, AIC, HQIC and SBIC. Following most previous studies, we rely mainly on the AIC as the optimal lag indicator. However, as shown by the results, in all cases, all the optimal lags selected are consistent across all the lag selection tests. However, this is not the case for the Crypto-currency Hedge

### Table 1

Descriptive statistics (variables are measured as the natural logarithm).

| Variable                  | No. of obs. | Mean     | Std. dev. | Min.  | Max.  |
|---------------------------|-------------|----------|-----------|-------|-------|
| Crypto-Currency Hedge Fund| 76          | 7.837    | 1.417     | 5.841 | 10.12 |

Hedge fund indices

| Hedge fund | No. of obs. | Mean     | Std. dev. | Min.  | Max.  |
|------------|-------------|----------|-----------|-------|-------|
| Global Hedge fund | 76          | 6.079    | 0.071     | 5.942 | 6.191 |
| Arbitrage  | 76          | 5.815    | 0.070     | 5.686 | 5.926 |
| Distressed Debt | 76         | 6.383    | 0.096     | 6.215 | 6.521 |
| Event Driven | 76         | 6.159    | 0.092     | 6.017 | 6.286 |
| Fixed Income | 76         | 5.939    | 0.077     | 5.810 | 6.076 |
| Long Short Equities | 76        | 6.054    | 0.086     | 5.909 | 6.190 |
| Macro      | 76          | 5.987    | 0.054     | 5.870 | 6.080 |
| Multi-Strategy | 76       | 6.162    | 0.074     | 6.016 | 6.281 |
| Relative Value | 76       | 6.134    | 0.079     | 6.003 | 6.244 |

Cryptocurrencies

| Crypto-currencies | No. of obs. | Mean     | Std. dev. | Min.  | Max.  |
|-------------------|-------------|----------|-----------|-------|-------|
| Bitcoin           | 57          | 7.876    | 1.278     | 5.440 | 9.560 |
| Ethereum          | 57          | 4.204    | 2.003     | -0.300 | 7.020 |
| Tether            | 57          | 0.0001   | 0.011     | -0.065 | 0.039 |
| COVID-19 pandemic | 76          | 0.066    | 0.249     | 0.000 | 1.000 |
Table 2
ADF unit roots tests with break points and BDS test.

| Variables                  | Level | p-Value | First Diff. | p-Value | BDS test |
|----------------------------|-------|---------|-------------|---------|----------|
|                            | Statistics | Break date |             | Statistics | Break date |             | BDS statistic | p-Value |
| LNCrypto                   | -3.544 | Feb. 2017 | (0.3627)    | -7.961*** | Dec. 2017 | (0.0001)    | 0.174***      | (0.0000) |
| LNHF                       | -0.314 | Jan. 2016 | (0.6016)    | -9.108*** | Jan. 2020 | (0.0001)    | 0.183***      | (0.0000) |
| LNArbitrage                | -2.793 | Feb. 2016 | (0.7907)    | -11.21*** | Jan. 2020 | (0.0001)    | 0.192***      | (0.0000) |
| LNCTA                      | -3.479 | Jul. 2014 | (0.3984)    | -10.98*** | Jan. 2020 | (0.0001)    | 0.163***      | (0.0000) |
| LNDistressed               | -3.564 | Feb. 2016 | (0.3506)    | -8.679*** | Feb. 2020 | (0.0001)    | 0.196***      | (0.0000) |
| LNEvent driven             | -3.443 | Nov. 2016 | (0.4175)    | -10.26*** | Jan. 2020 | (0.0001)    | 0.189***      | (0.0000) |
| LNFIXED                    | -3.154 | Feb. 2016 | (0.5946)    | -14.54*** | Feb. 2020 | (0.0001)    | 0.187***      | (0.0000) |
| LNLongshort                | -3.503 | Dec. 2016 | (0.3853)    | -8.801*** | Dec. 2019 | (0.0001)    | 0.173***      | (0.0000) |
| LNMACRO                    | -2.706 | Dec. 2018 | (0.8284)    | -9.508*** | Feb. 2020 | (0.0001)    | 0.181***      | (0.0000) |
| LNMultistrategy            | -3.288 | Feb. 2016 | (0.5103)    | -9.557*** | Jan. 2020 | (0.0001)    | 0.181***      | (0.0000) |
| LNRelative                 | -3.809 | Feb. 2016 | (0.2318)    | -8.870*** | Jan. 2020 | (0.0001)    | 0.191***      | (0.0000) |
| LNBitcoin                  | -3.558 | Apr. 2017 | (0.3549)    | -7.685*** | Dec. 2017 | (0.0001)    | 0.188***      | (0.0000) |
| LN Ethereum                | -3.536 | Jan. 2017 | (0.3673)    | -6.960*** | Mar. 2018 | (0.0000)    | 0.182***      | (0.0000) |
| LNetherether               | 12.911 | Apr. 2017 | (0.0000)    | -13.49*** | Aug. 2016 | (0.0000)    | 0.099***      | (0.0037) |

Test critical values

1% level -4.949
5% level -4.444
10% level -4.194

Note: BDS statistic denotes the Brock-Dechert-Scheinkman test for non-linearity proposed by Brock et al. (1987) for testing against a variety of possible deviations from independence including non-linear dependence and chaos. It is defined as $BDS(\delta,m,T) = \sqrt{T} \left( C(\delta, m, T) - C(\delta, 1, T) \right)$, where $C(\delta, m, T)$ as a U-statistics, is a minimum unbiased variance while $\sigma(\delta,m,T)$ is a nontrivial function of the correlation integral. Lastly, *** represents significance at the 1% level.

Table 3
Lag selection.

| VAR model                        | FPE | AIC | HQIC | SBIC |
|----------------------------------|-----|-----|------|------|
| Crypto-Currency Hedge Fund vs. Global Hedge fund | 1   | 1   | 1    | 1    |
| Crypto-Currency Hedge Fund vs. Arbitrage       | 2   | 2   | 1    | 1    |
| Crypto-Currency Hedge Fund vs. Distressed Debt | 1   | 1   | 1    | 1    |
| Crypto-Currency Hedge Fund vs. Event Driven   | 1   | 1   | 1    | 1    |
| Crypto-Currency Hedge Fund vs. Fixed Income   | 1   | 1   | 1    | 1    |
| Crypto-Currency Hedge Fund vs. Long Short Equities | 1   | 1   | 1    | 1    |
| Crypto-Currency Hedge Fund vs. Macro          | 1   | 1   | 1    | 1    |
| Crypto-Currency Hedge Fund vs. Multi-Strategy | 1   | 1   | 1    | 1    |
| Crypto-Currency Hedge Fund vs. Relative Value | 1   | 1   | 1    | 1    |

Table 4
Johansen cointegration test results.

| VAR model                        | Max. rank | Trace STATISTICS | 5% Critical value |
|----------------------------------|-----------|------------------|-------------------|
| Crypto-Currency Hedge Fund vs. Global Hedge fund | 0         | 13.78            | 15.41             |
| Crypto-Currency Hedge Fund vs. Arbitrage       | 0         | 8.507            | 15.41             |
| Crypto-Currency Hedge Fund vs. Distressed Debt | 0         | 7.546            | 15.41             |
| Crypto-Currency Hedge Fund vs. Event Driven   | 0         | 11.87            | 15.41             |
| Crypto-Currency Hedge Fund vs. Fixed Income   | 0         | 9.634            | 15.41             |
| Crypto-Currency Hedge Fund vs. Long Short Equities | 0     | 14.27            | 15.41             |
| Crypto-Currency Hedge Fund vs. Macro          | 0         | 9.868            | 15.41             |
| Crypto-Currency Hedge Fund vs. Multi-Strategy | 1         | 0.813            | 3.76              |
| Crypto-Currency Hedge Fund vs. Relative Value | 0         | 11.83            | 15.41             |

Fund vs Arbitrage model where the SBIC indicates an optimal lag of 1 while the other three lag selection tests suggest 1. Following the usual practice, we accept the optimal lag length that consistent across a higher number of selection tests. Consequently, Lag 1 is used for Crypto-Currency Hedge Fund vs Global Hedge fund; Distressed Debt; Event Driven; Fixed Income; Long Short Equities; Macro; Multi-Strategy; and Relative Value VAR models. However, Lag 2 is used for Crypto-Currency Hedge Fund vs Arbitrage model.

Table 4 presents the results for Johansen test between Crypto-Currency hedge fund and all hedge funds indices. The number of cointegration relationships between variables is determined according to trace value. The results indicate that we can accept the null hypothesis of no cointegrating vectors between Cryptocurrency Hedge Fund and each of these hedge funds indices: Global Hedge fund, Arbitrage, Distressed Debt, Event Driven, Fixed Income, Long Short Equities, Macro and Relative Value. However, we reject the null hypothesis for Crypto-Currency Hedge Fund vs Multi-Strategy. Indeed, there is one cointegration rank which is significant at 5%. Hence, we conclude that there is a long-term equilibrium relationship between cryptocurrency Hedge Fund and Multi-Strategy.

The next step of our analysis is to create VAR models and test Granger causality. These tests can be applied only for two non-cointegrated variables (which are mentioned in the previous paragraph). The results of this analysis are displayed in Table 5. The diagnostics which confirms both the normality and stability conditions of these models are presented in Tables 9 and 10 using the Jarque-Bera and Langrange Multiplier (LM) tests. Based on the result for cryptocurrency Hedge Fund vs Global Hedge fund, the p-value for the first null hypothesis is lower than significance value of 5%, while the p-value of the second one is equal to 10%. Hence, we reject the first null hypotheses but accept the second, meaning that Crypto-Currency Hedge Fund Granger-cause Global Hedge fund while Global Hedge fund does not Granger-cause cryptocurrency Hedge Fund.

This relationship can be explained by the fact that there is interaction between Crypto-Currency and conventional hedge funds. Particularly, among hedge funds strategies, the Granger causality tests also suggest that there is interaction between the Crypto-Currency Hedge Fund and each of the following indices: Long Short Equities and Relative Value. However, we find three simple Granger causal relationships from Arbitrage, Fixed Income and Macro to cryptocurrency Hedge Fund, indicating that this latter is influenced by the fluctuations of Arbitrage, Fixed Income and Macro. Finally, only two Granger causal relationships can be found at the 5% level, as lagged values of Cryptocurrency Hedge Fund significantly predict both Distressed Debt and Event Driven.
A number of economic interpretations may be derived from the above results. For instance, the finding that causal relationships run from cryptocurrency hedge funds to some traditional funds strategies including Distressed Debt and Event Driven suggest that returns on these investment funds may be affected by price changes in the cryptocurrency market. This is particularly important due to the continuous evolution and high volatility in the prices of cryptocurrencies in recent times. Given that an increasing stream of empirical studies has emerged documenting substantial risk spillover and predictability from the cryptocurrency market to other traditional assets, these findings suggest that returns for these hedge fund strategies may be affected by risks from the cryptocurrency market, especially during extreme market periods. However, some studies have also shown that during bearish market times, cryptocurrencies may exhibit negative dependence with other asset classes, implying that they may act as safe havens for these assets. This suggests that Distressed Debt and Event Driven funds managers may benefit from the inclusion of cryptocurrencies in their portfolio during bearish market periods.

In contrast, the findings of causal interactions from the Global, Arbitrage, Fixed income and Macro hedge funds to cryptocurrency hedge fund suggest that developments from these investment strategies has noticeable effects on returns from the market for cryptocurrencies. Hence, digital currency hedge fund managers would minimize their own strategies. To reduce risks and increase returns by reducing the level of risk spillovers from either hedge fund strategy, this result suggests that Distressed Debt and Event Driven funds managers would minimize their own strategies. As noted in Bali, Brown, and Demirtas (2013), traditional hedge funds make extensive use of derivatives, short selling, and leverage and their dynamic trading strategies create significant nonnormalities in their return distributions, fundamental performance approaches fail to deliver accurate description of the relative strength of hedge fund portfolios.

This suggests that it may be relatively difficult for cryptocurrency hedge fund managers to accurately predict and incorporate the expected outcome from the investment strategies of the Global, Arbitrage, Fixed income and Macro hedge funds managers. Lastly, results also show that causality runs from both the relative value and cryptocurrency hedge funds to each other. To reduce risks and increase returns by reducing the level of risk spillovers from either hedge fund strategy, this result suggests that the managers of each of these hedge funds will benefit from predicting and incorporating the investment strategies of each other in their own strategies.

We explore the impact of Covid-19 crisis on the fluctuations of hedge funds indices by including crisis dummy variable as explanatory variable in each VAR model. The results show that the COVID-19 crisis has significant negative impact only for Event Driven index, Relative Value index and Distressed Debt index as reflected by a significant drop in their values during this critical period. Given that we found a cointegration relationship between cryptocurrency Hedge Fund and Multi-strategy, we proceed with the VECM. Results are provided in Table 6.

Table 7
ARDL bounds test.

| H0: No levels relationship | F = 0.621 | t = 1.829 |
|--------------------------------|---------|----------|
| Critical Values (0.1–0.01), F-statistic, Case 3 | [1.0, 0.1, 0.01] | [1.0, 0.1, 0.01] |
| K 7 | 2.03 3.13 | 2.32 3.50 | 2.60 3.84 | 2.96 4.26 |
| Critical Values (0.1–0.01), t-statistic, Case 3 | [1.0, 0.1, 0.01] | [1.0, 0.1, 0.01] |
| K 7 | 2.57 4.23 | 2.86 4.57 | 3.13 4.85 | 3.43 5.19 |

Cryptocurrency Hedge Fund’s coefficient is negative and significant –0.076. However, the Multi-Strategy’s coefficient is positive and significant 0.005. These suggest that Crypto-Currency Hedge Fund’s values exert stronger influence than Multi-Strategy’s values. Hence, an increase in the last period’s equilibrium leads to a decrease in the current period. Both hedge funds indices contribute to the price movement of each, indicating the presence of a bi-directional relationship between both hedge fund strategies.

Concerning the impact of mainly traded cryptocurrencies on the cryptocurrency hedge fund using ARDL technique, we begin by identifying the lag order for the model. The optimal lag order of each variable in the model is determined using SBIC. According to the length of sample data, the maximum lagorderforeachvariableislimitedto1. Thus, ARDL (10110010)is the most appropriate. Secondly, Augmented Dickey Fuller test is carried out on the stationarity of the different variables. The findings suggest that all series are all non-stationary, but turned into stationary variables after first-order difference. Hence, I(1) is stationary and we can employ the ARDL model. Also, we study the joint F-significance test for equation against the critical value of Pesaran et al. (2001).

Table 8
ARDL estimation results.

| ARDL (10110010) |
|-------------------|
| Dependent variable: D Crypto-currency hedge funds |
| Explanatory variables | Coefficient |
| Δ Crypto-currency hedge funds(-1) | 0.846*** (10.08) |
| COVID-19 crisis | 3.415 (0.910) |
| Bitcoin | 0.680*** (10.67) |
| Δ Bitcoin(-1) | -0.578*** (-6.500) |
| Ethereum | 0.159*** (4.890) |
| Δ Ethereum(-1) | -0.128*** (-3.550) |
| Bitcoin*Covid-19 crisis | -0.592 (-0.730) |
| Ethereum*Covid-19 crisis | 0.369 (0.440) |
| Tether | 0.105 (0.100) |
| Δ Tether(-1) | 0.599 (0.570) |
| Tether*Covid-19 crisis | -5.947 (-0.250) |
| C | 0.351 (1.550) |
| N | 56 |
| R-squared | 0.996 |

*,,*** represent the thresholds of significance and which are respectively 1%, 5% and 10%.
The results of the bounds test for cointegration reported in Table 7 suggest that there is no cointegrating relationship among all variables of the study. Indeed, the calculated F-statistic value (0.621) is lower than the critical values, indicating no existence of long-run relationship among cryptocurrency hedge funds, COVID-19 crisis, Bitcoin, Ethereum and Tether.

Following the results that these variables are found not to be cointegrated, we proceed to estimate the ARDL model. The results from the ARDL model is presented in Table 8, showing the findings on the relationship between cryptocurrency hedge funds and each of cryptocurrencies including Bitcoin, Ethereum and Tether why accounting for the effects of the COVID-19 pandemic. As may be seen, results suggest that the coefficients associated with Bitcoin and Ethereum are positive and significant at 1%, suggesting that cryptocurrency hedge fund managers investment strategies are positively impacted by the prices these two cryptocurrencies. In particular, the results suggest that if the value of Bitcoin and Ethereum grow by 1%, the cryptocurrency hedge funds’ value will grow by about 6.38% and 3.24%, respectively.

However, the results show that the coefficient associated with the COVID-19 pandemic appear not to be statistically significant, suggesting that the pandemic may not have had any significant impact on cryptocurrency hedge funds’ value. More importantly, these results are also corroborated by the non-statistical significant coefficients of the interaction terms of the COVID-19 crisis with both Bitcoin and Ethereum. This further suggest that the COVID-19 pandemic did not significantly alter the effects of Bitcoin and Ethereum values on cryptocurrency hedge funds strategies. Lastly, we find that the coefficient associated with the third cryptocurrency namely, Tether appear not to be statistically significant. This implies that the effect of Tether on cryptocurrency hedge funds strategy is not significant and that the COVID-19 crisis did not change this result as shown by the coefficient of the interaction term. Taken together, these results suggest that cryptocurrency hedge fund managers allocate to Bitcoin and Ethereum but not to Tether.

Intuitively, results from the ARDL analysis show some important economic and financial interpretations. For instance, the findings of positive significant effects of both Bitcoin and Ethereum on cryptocurrency hedge fund strategies suggest that price changes in these digital currencies have substantial effects on returns for cryptocurrency hedge fund managers. As expected, the effect of Bitcoin is relatively stronger as shown by the coefficients, implying that changes in Bitcoin’s market value mainly drive the performances of investors in the cryptocurrency fund space. This is expected given that Bitcoin remains the most popular digital currency both in terms of price and market capitalization. This also implies that the high price volatility exhibited by bitcoin especially in recent times, presents a more risky future for cryptocurrency fund managers. Moreover, as we control for the COVID-19 pandemic, these results suggest that similar global health crisis may not alter the aggregate level of risks from the Bitcoin and Ethereum market liquidity, volatility, reversals and momentum on the performance of cryptocurrency hedge fund managers.

4. Conclusion

The novel coronavirus has rapidly developed from a major health scare to a worldwide collapse, which raises concerns for many investors, policy makers and all financial markets participants. This paper provides an original statistical analysis of the relationship between cryptocurrency market and hedge funds in two distinct ways. In the first step, we investigate the connectedness between Cryptocurrency hedge funds.
Table 5
Granger causality test results.

| VAR model | $\chi^2$ | p-Value | Causality relationship |
|-----------|---------|---------|------------------------|
| Global Hedge fund do not Granger-cause Crypto-Currency Hedge Fund | 4.348** | (0.037) | Global Hedge fund $\Rightarrow$ Crypto-Currency Hedge Fund |
| Crypto-Currency Hedge Fund do not Granger-cause Global Hedge fund | 2.697 | (0.100) | |
| Arbitrage do not Granger-cause Crypto-Currency Hedge Fund | 6.078** | (0.048) | Arbitrage $\Rightarrow$ Crypto-Currency Hedge Fund |
| Crypto-Currency Hedge Fund do not Granger-cause Arbitrage | 1.794 | (0.408) | |
| Distressed Debt do not Granger-cause Crypto-Currency Hedge Fund | 0.099 | (0.753) | Crypto-Currency $\Rightarrow$ Hedge Fund Distressed Debt |
| Crypto-Currency Hedge Fund do not Granger-cause Distressed Debt | 5.788** | (0.016) | |
| Event Driven do not Granger-cause Crypto-Currency Hedge Fund | 1.606 | (0.205) | Crypto-Currency Hedge Fund $\Rightarrow$ Event Driven |
| Crypto-Currency Hedge Fund do not Granger-cause Event Driven | 5.815** | (0.016) | |
| Fixed Income do not Granger-cause Crypto-Currency Hedge Fund | 3.111* | (0.078) | Fixed Income $\Rightarrow$ Crypto-Currency Hedge Fund |
| Crypto-Currency Hedge Fund do not Granger-cause Fixed Income | 1.226 | (0.268) | |
| Long Short Equities do not Granger-cause Crypto-Currency Hedge Fund | 2.729* | (0.099) | Crypto-Currency Hedge Fund $\Rightarrow$ Long Short Equities |
| Crypto-Currency Hedge Fund do not Granger-cause Long Short Equities | 5.384** | (0.020) | |
| Macro do not Granger-cause Crypto-Currency Hedge Fund | 3.673* | (0.055) | Macro $\Rightarrow$ Crypto-Currency Hedge Fund |
| Crypto-Currency Hedge Fund do not Granger-cause Macro | 0.865 | (0.352) | |
| Relative Value do not Granger-cause Crypto-Currency Hedge Fund | 4.134** | (0.042) | Relative Value $\Rightarrow$ Crypto-Currency Hedge Fund |
| Crypto-Currency Hedge Fund do not Granger-cause Relative Value | 3.238* | (0.072) | |

* ** denotes the thresholds of significance and which are respectively 1%, 5% and 10%.

and conventional hedge funds strategies. In the second step, we analyse the impact of cryptocurrency price changes on cryptocurrency hedge funds' values during COVID-19 crisis. The empirical results demonstrate that there are significant interactions among cryptocurrency and conventional hedge funds strategies.

Particularly, among hedge funds strategies, we document evidence of causal interactions from cryptocurrency hedge fund to Distressed debt and Event Driven hedge fund strategies while causality runs from Global, Arbitrage, Fixed Income and Macro hedge fund strategies to the cryptocurrency hedge fund market. However, we found also that there are mutual causal relationship between cryptocurrency hedge funds and Long Short Equities hedge funds and between cryptocurrency hedge fund and Relative Value hedge fund strategies. Moreover, our findings suggest also that the COVID-19 pandemic has significant negative impact on the the following hedge funds: Event Driven, Relative Value and Distressed Debt as reflected in significant decrease in their values during this critical period.

Besides, our further analysis suggest that cryptocurrency hedge funds' managers allocate investments to Bitcoin and Ethereum as shown by significant impact of these digital currencies on the performance of cryptocurrency hedge fund strategy. Using some interaction terms, we provide convincing evidence the COVID-19 pandemic has no significant effect on the effects of Bitcoin and Ethereum on the performance of cryptocurrency hedge funds investment strategy. These empirical results offer prominent implications for hedge funds managers and the wider investors in the digital currency market space. For instance, it provides crucial information for conventional hedge funds managers and cryptocurrency market key players for understanding the dependencies between these markets during global pandemics such as the COVID-19.

In particular, the evidence of causal relationship between cryptocurrency hedge fund and traditional hedge fund strategies imply that both markets exhibit some crucial information that are useful for forecasting each other. For instance, the finding that a causal relationship runs from cryptocurrency hedge fund to Distressed Debt and Event Driven imply that the lagged performance of cryptocurrency hedge funds contain statistically significant information about the future value of these traditional hedge fund strategies. Therefore, investors that are interested in forecasting the performance of Distressed Debt and Event Driven hedge fund may benefit from observing the past performance of cryptocurrency hedge fund strategies. Similarly, investors may benefit from observing the past performance traditional hedge fund strategies including Global, Arbitrage, Fixed income and Macro hedge fund strategies as they contain significant information about future performance of cryptocurrency hedge fund strategies.

Concerning the mutual causal relationships among Long Short Equities, Relative Value and cryptocurrency hedge funds, the implication of these results is that each market contain useful information for forecasting the future values of other markets. Therefore, investors in each of these markets may benefit from incorporating the past performance of each market into the forecasting model for the future performance of the other markets. Moreover, these results also have some benefits for investors who may be interested in portfolio diversification. For instance, the presence of causal relationships between cryptocurrency hedge funds and the conventional fund strategies included in these analysis suggests that the inclusion of these instruments may not offer investors optimal portfolio diversification benefits.

This is even more crucial in the instance of mutual causal relationships, which exist among cryptocurrency, Long Short Equities and Relative Value funds strategies. The implication of these results is that past poor performances in any of these instruments has the potential of negatively influence the future performance of any of the remaining two investment strategies. Regarding our findings on the significant impacts of the mainly traded digital currencies including Bitcoin and Ethereum on cryptocurrency fund, this result imply that cryptocurrency funds managers mainly allocated investments to these two currencies. This is not unexpected because these are the two most actively traded and capitalized cryptocurrencies. Besides, the statistically insignificant impact of the COVID-19 on the performance of the cryptocurrency fund strategy suggests that during the period of the pandemic, the performance of the cryptocurrency hedge fund appear to have been mainly driven by price changes in the underlying cryptocurrencies, especially Bitcoin. However, given the noticeable increase in mining and trading of other emerging currencies, this study would recommend the allocation of investments to these currencies by cryptocurrency hedge fund managers as an approach towards greater portfolio diversification.

Authors' statement

The authors declare no conflict of interest regarding this paper.

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