Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company’s public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
The effect of COVID-19 pandemic on return-volume and return-volatility relationships in cryptocurrency markets

Parisa Foroutan, Salim Lahmiri *

Department of Supply Chain and Business Technology Management, Concordia University, Montreal, Canada

ABSTRACT

Understanding the dynamics of cryptocurrency markets during financial crises such as the recent one caused by the COVID-19 pandemic is crucial for policy makers and investors. In this study, the effect of COVID-19 pandemic on the return-volatility and return-volume relationships for the ten most traded cryptocurrencies, namely Tether, Bitcoin, Ethereum, Ripple, Litecoin, Bitcoin Cash, EOS, Chainlink, Cardano, and Monero is examined. Further, the behavior of cryptocurrencies during COVID-19 pandemic is compared with less volatile markets such as Gold, WTI, and BRENT crude oil markets. To study the effect of volatility on cryptocurrency return, an EGARCH-M model is employed while for the return-volume relationships the VAR model and Granger causality tests are utilized. Results show that the return-volatility relationships for Tether, Ethereum, Ripple, Bitcoin Cash, EOS, and Monero are significant during COVID-19 pandemic, while the same relationship is not significant prior to the pandemic for any of the studied cryptocurrencies. Our findings of the return-volume relationship support the availability of causal relations from return to trading volume changes for Chainlink and Monero in the pre-COVID-19 period and for Ethereum, Ripple, Litecoin, EOS, and Cardano during the COVID-19 period. However, considering the absolute values of returns, we found a significant relationship from cryptocurrencies’ absolute returns to trading volume changes for both the prior and during COVID-19 periods. From a managerial perspective, gold can be considered a suitable asset for portfolio hedging during the pandemic period and trading volume can help traders and investors identify the effect of momentum and potential trend in cryptocurrencies on their investments.

© 2022 Elsevier Ltd. All rights reserved.

Keywords: Cryptocurrency Return-volume relationship Return-volatility relationship COVID-19 pandemic Granger causality EGARCH-M

1. Introduction

Cryptocurrencies are recently emerged financial markets that are growing rapidly due to their ability to facilitate direct, transparent, and secure blockchain-based electronic payments between individuals all around the world. Bitcoin is the first known decentralized cryptocurrency that was founded in 2009 by a pseudonymous programmer Satoshi Nakamoto (www.investopedia.com). As of November 15, 2021, the global cryptocurrency market capitalization is $2809.5 billion with 7381 cryptocurrencies (www.coinmarketcap.com) among which Bitcoin has the highest market capitalization of $1210 billion (43.09 % of the total cryptocurrency market capitalization). As digital cryptocurrencies are getting more popular among governments, companies, and individuals, there are more traders, investors, and scholars who focus on improving their knowledge about the characteristics of these markets and forecasting their future potential returns on investments.

There is a limited knowledge about the behavior of cryptocurrencies during the financial crisis as these digital currencies have been developed after the last global recession in 2008. The most recent global distress has been COVID-19 disease, which was first detected in Wuhan, China on December 31, 2019, and was subsequently declared a global pandemic by the World Health Organization (WHO) on March 11, 2020 [1]. Governments enforced many immediate measures such as quarantines, lockdowns, and social distancing to reduce the number of confirmed and death cases due to the pandemic. COVID-19 outbreak was a fierce threat that dramatically affected the world economy as many companies were shut down, sales and productions fell, and unemployment rates surged, leading to downward movement in the majority of the industries.

Considering that the COVID-19 pandemic is an unforeseen crisis, many researchers scrutinized the effect of this pandemic on financial markets properties and relationships [2–5]. Among these markets, cryptocurrencies are the new digital currencies with many unrecognized characteristics that need to be investigated. For instance,
the authors in [6] studied the asymmetric efficiency of four cryptocurrencies and found that significant amounts of market inefficiency can appear in periods of a global health crisis. The implication of COVID-19 confirmed and death cases on market prices of cryptocurrencies is examined in [7] showing that increased number of daily COVID-19 confirmed, and death cases have a direct effect on these markets’ prices.

A considerable stream of the recent literature about the effect of COVID-19 on cryptocurrencies has examined the safe-haven properties of cryptocurrencies for investment portfolio hedging during the COVID-19 pandemic. Studies in [8-10] show that cryptocurrencies can be a potential safe-haven asset for the stock market, commodity market, and forex market during periods of financial market crisis due to the COVID-19 while empirical evidence suggests that Ethereum is a better safe-haven than Bitcoin [8,9]. In another study [11], the effect of cryptocurrency price changes on the conventional and cryptocurrency hedge funds was examined during the COVID-19. The empirical results indicate that the COVID-19 crisis has a significant negative effect on the performance of conventional hedge funds while it did not significantly affect the performance of cryptocurrency hedge funds investing in either Bitcoin or Ethereum. It is worth to mention that other works have studied the effect of COVID-19 on financial markets specially the cryptocurrency markets by using Granger causality tests [2,12], VAR, VECM, ARDL, and ARDL-ECM [11,13], and ARFIMA and FIGARCH models [14].

Regarding return-volatility relationship, several studies have been conducted in finance literature [15-17] where evidence of a negative and asymmetric relationship was reported. In this regard, volatility is often referred to as a proxy of the investor’s fear [18]. A growing literature has empirically examined the cryptocurrencies price volatilities. An empirical study on 45 cryptocurrencies shows that cryptocurrencies are more unstable and more irregular during the COVID-19 pandemic compared to international stock markets [19]. Likewise, evidence from EGARCH model suggests that the leverage effect is significant for Litecoin, Ripple, and Ethereum, but not for Bitcoin [20]; and that Bitcoin volatility is highly unstable in speculative periods compared to stable ones [1,21]. Moreover, the effect of news on the predictability of return volatility of cryptocurrency market during the COVID-19 pandemic is examined by a GARCH-MIDAS framework which indicates that the return volatility of digital currencies is riskier during the pandemic [22,23].

Besides, understanding the relationship between price and volume of financial markets has been an important subject of study among researchers as it provides insights into the structure of markets and it is important for event studies that use a combination of stock returns and trading volume data to make inferences [24]. Trading volume is linked to investor attention and reveals how investors react to news about the firm or the asset [25]. Moreover, trading volume describes investor’s learning curve that causes overconfidence and further alters future stocks returns in [26,27]. The Sequential Arrival of Information (SAI) model [27] states that information is spread sequentially, and trading volume is a proxy for the information flow rate, implying a positive correlation between volume and the absolute value of price changes which is supported by the mixture of distributions model [29].

Existing works provide various analyses and findings regarding the dynamic relationship between return and trading volume. For instance, a positive correlation between stock market trading volume and the absolute value of return was found in [30,31], while it was shown that trading volume does not Granger-cause stock returns [32]. In a more recent study [33], the information transfer between stock prices and trading volume is investigated using Shannon transfer entropy which confirms a significant nonlinear information transfer from stock returns to trading volume changes.

Although the causal relations between trading volume and stock returns have been widely investigated in the literature, there is limited empirical research to examine these relationships in the cryptocurrency markets. Most recently, the relationship between cryptocurrency returns and liquidity has been found significant in the period after the COVID-19 outbreak while the returns are found to significantly impact the volume changes before COVID-19 outbreak [34]. However, in [34], only the short-term effect of the outbreak is considered as the sample only covers the data up to May 27, 2020. Likewise, Leirvik, 2021 found a significant but time-varying correlation between cryptocurrency liquidity volatility and returns [35].

Despite all efforts by scholars, there is still a lack of knowledge about cryptocurrencies’ volatility-return relationship during the COVID-19 pandemic. In this study, we fill this gap in the literature by utilizing an ARMA-EGARCH model to examine the effect of return volatilities on the ten most traded cryptocurrency market returns prior to and during the COVID-19 outbreak. More particularly, we will test whether there is a difference in cryptocurrencies’ returns due to their return volatility in pre-COVID-19 and during COVID-19 periods. Since cryptocurrency markets are highly volatile in nature, this effect will be compared with the return and volatility of crude oil and gold commodities for the same periods. The COVID-19 risk is perceived differently over the short and the long-run and may be regarded as an economic crisis in the early stages of its emergence. In this regard, a time frame of one year prior to the COVID-19 pandemic and one year during this pandemic is considered to capture both short and relatively long-term effects.

In addition, we study the unidirectional and bidirectional Granger causality relationship between the ten most traded cryptocurrency returns and trading volume changes and further to test the effect of COVID-19 pandemic on these relationships. This analysis will help explain these relationships in the prior-COVID-19 pandemic and during the COVID-19 pandemic periods and allow a more comprehensive interpretation of digital currency market movements. To the best of our knowledge, none of the previous studies have compared return and volume change relationships prior and during COVID-19 pandemic, so the current study seeks to remedy this situation.

In summary, our study makes the following important contributions to the existing literature on the effect of COVID-19 pandemic on the dynamics of cryptocurrencies and commodity markets:

1. As the COVID-19 pandemic is the first global crisis after the advent of cryptocurrencies, it is important to examine the behavior of digital currencies during this distress. This study analyzes and compares cryptocurrency dynamics in the prior and during COVID-19 pandemic periods which has received limited attention compared to the conventional financial markets.

2. We examine the effect of return volatilities on the ten most traded cryptocurrency market returns prior to and during the COVID-19 outbreak. Such investigation would help understanding the risk reward in cryptocurrency markets before and during COVID-19 pandemic.

3. We compare cryptocurrencies’ return-volatility relationships with the same relationship in some commodity markets such as crude oil and gold for pre-COVID-19 and during-COVID-19 pandemic. This comparison will give some insights to investors for distinguishing the associated risk with cryptocurrencies and commodity markets and will enable them to decide their positions during the COVID-19 pandemic.

4. In contrast to the existing literature that limit their analysis to a small number of cryptocurrency markets, mainly Bitcoin and Ethereum, our study evaluates the ten most traded cryptocurrency markets to have a better and generalized idea of digital currency markets as well as investigating crude oil and gold markets.

5. We consider almost the same sample size for both periods of prior and during COVID-19 pandemic to ensure that there will not be any estimation bias related to sample size. Moreover, our empirical study will cover longer period during COVID-19 pandemic compared to the other similar studies.

6. The results from our study would assist investors to compare the potential risk of investing in crypto markets with other commodity
markets during the COVID-19 pandemic and develop investment strategies by considering the return-volatility and return-volume relationships.

To this end, we focus on investigating the relationship between cryptocurrencies’ returns and volatility of returns by employing autoregressive conditional heteroscedasticity in mean model (EGARCH-M) [36,37] along with examining the significance and direction of cryptocurrency return and volume changes by utilizing VAR models and Granger Causality tests [44].

The remainder of this manuscript is organized as follows. The methodology is described in Section 2. Section 3 provides the data and discusses the empirical results. Finally, Section 4 concludes the paper.

2. Methodology

In this study, return and volume change series are defined as follows:

\[ R_t = 100 \times \log \left( \frac{P_{t+1}}{P_t} \right) \] (1)

\[ V_t = \log \left( \frac{V_{t+1}}{V_t} \right) \] (2)

where \( P_t \) and \( V_t \) are, respectively, the price and trading volume of the asset at time \( t \).

2.1. Return-volatility relationships

To investigate the effect of the COVID-19 pandemic on the return-volatility relationship, the EGARCH-M [36] is employed while the mean returns are estimated by utilizing the Autoregressive Moving Average (ARMA) model [38]. The formulation of the EGARCH(1,1) in mean model studied in this study is:

\[ r_t = c + \sum_p \varphi_p r_{t-p} + \sum_q \theta_q \epsilon_{t-q} + \lambda \alpha \epsilon_t^2 + \epsilon_t = z_t \sigma_t, \quad \text{and} \]

\[ \ln \left( \sigma_t^2 \right) = \omega + \alpha_1 (z_{t-1}) + \beta \ln \left( \sigma_{t-1}^2 \right) \] (4)

In Eq. (3) \( c \) is the constant intercept, \( \epsilon_t \) is the error term, \( \sigma_t^2 \) is the conditional variance, and \( \varphi_p \) and \( \theta_q \) are the parameters of autoregressive and moving average terms, respectively.

The structure of ARMA models for each market in pre-COVID-19 and during-COVID-19 periods are determined according to the Ljung-Box Q-test for autocorrelations [39] and the Akaike Information Criterion (AIC) [40]. EGARCH-in-mean parameter (\( \lambda \)) captures the impact of return volatility on cryptocurrency returns. Similarly, in Eq. (4) for the EGARCH(1,1) model, \( \omega \) is the constant intercept, \( \alpha_1 \) is the scale of the asymmetric volatility, \( \alpha_2 \) is the scaled absolute value of last period’s volatility shock, and \( \beta \) is the coefficient for the log of the GARCH term. The maximum likelihood estimation (MLE) routine [41] is employed to estimate all parameters of the EGARCH process.

2.2. Return-volume relationships

In order to find the return-volume change relationships, first a vector autoregression (VAR) model [42] is created and then a Granger causality test is performed on the estimated coefficients for the VAR model. This model can be expressed as:

\[ R_t = a_t + \sum_{i=1}^{m} b_{it} R_{t-i} + \sum_{i=1}^{m} c_{it} V_{t-i} + \epsilon_{rt} \] (5)

\[ V_t = a_v + \sum_{i=1}^{p} b_{v,i} R_{t-i} + \sum_{i=1}^{p} c_{v,i} V_{t-i} + \epsilon_{vt} \] (6)

where \( R_t, V_t, \epsilon_{rt}, \epsilon_{vt}, \) and \( R_{t-i}, V_{t-i} \) are error terms and \( m \) and \( p \) denote the autoregressive and moving average lag lengths. The optimal lag structures in Eq. (5) and Eq. (6) are chosen according to the corresponding AIC. Recall that Eq. (5) and Eq. (6) have been estimated by using MLE method.

The variables in a VAR model should be stationary so that the VAR estimates be reliable. For this, the Augmented Dicky Fuller (ADF) test [43] is performed in which the null hypothesis is that series have a unit root. Replacing the null hypothesis signifies that series are stationary.

If the null hypothesis that \( c_i \)’s jointly equal zero is rejected, it is argued that volume change Granger causes returns [44]. Similarly, if the null hypothesis that \( b_i \)’s jointly equal zero is rejected, returns Granger cause volume change. If both null hypotheses are rejected, a bidirectional Granger causality exists between variables.

To get a common understanding of the behavior of the above-mentioned markets, first descriptive analysis of returns, volatility, and volume change for pre-COVID-19 and during COVID-19 pandemic periods is performed. Then results of statistical tests involving simple Pearson correlations between the returns and volume changes for both periods at 5% significance level will be presented. Additionally, Granger causality tests are applied to investigate any lead-lag relation between volume change and return time-series. The optimal number of lags has been determined by minimizing the AIC. Hence, we test whether the cryptocurrency returns “Granger cause” its trading volume and vice-versa.

3. Data and empirical results

3.1. Data

In this paper, thirteen markets including ten cryptocurrencies, Gold, and West Texas Intermediate (WTI), and BRENT Crude Oil markets are studied. Accordingly, daily closing prices of the ten most traded cryptocurrencies (as in the last three months of 2020), daily prices of Gold, and WTI, and BRENT Crude Oil prices are collected for a period from January 01, 2019 to December 31, 2020. The cryptocurrencies studied in this paper are Tether, Bitcoin, Ethereum, Ripple, Litecoin, Bitcoin Cash, EOS, Chainlink, Cardano, and Monero. According to the Wuhan Municipal Health Commission report to the WHO, the first COVID-19 confirmed cases was on December 31, 2019, therefore, the full sample of each market is split into two subsamples. The period from January 01, 2019 to December 31, 2019 is considered as pre-COVID-19 pandemic period, while the period from January 01, 2020 to December 31, 2020 is during COVID-19 pandemic. The pandemic period is just considered the 2020 year to ensure sample sizes for pre-pandemic and during pandemic periods are comparable for the current analysis. In general, cryptocurrency prices are available for seven days of a week while the WTI, BRENT, and gold prices are only available for five days a week.

Table 1 shows the sample size and source of datasets.

Table 1

| Market              | 2019 sample (prior-Covid19) | 2020 sample (during-Covid19) | Data source                      |
|---------------------|----------------------------|-------------------------------|---------------------------------|
| Cryptocurrencies    |                            |                               |                                 |
| WTI and BRENT Crude Oil | 365 | 361 | Yahoo Finance                |
| Gold                | 248                         | 246                           | Thomson Reuters from the U.S. Energy Information Administration |
| West Texas Intermediate (WTI) | 248 | 246 | World Gold Council           |
returns ranged from 0.0001 to 0.2221 %, with Tether having the least and Chainlink having the most return. Chainlink is the most volatile among the cryptocurrencies considered in both prior and during COVID-19. Further, the standard deviations of all analyzed markets are higher during the pandemic, indicating that, in general, returns are more volatile during the pandemic, with Chainlink being the most volatile among the cryptocurrencies considered in both prior and during COVID-19. Moreover, during the pandemic, all markets’ return distributions, except for Tether, are negatively skewed with high excess kurtosis showing that the return series are not normally distributed. By looking at the maximum and minimum returns, it can be concluded that the return range of all markets is larger during the pandemic, compared to the pre-pandemic period. Table 1 also reports the kurtosis and skewness of the return distributions in 2019 and 2020. These results show that in both periods, the return distributions are non-normal, and they represent excess kurtosis and negative skewness in both prior and during pandemic periods. The excess kurtosis and negative skewness are more extreme for the return distributions during the pandemic. This confirms the presence of volatility and GARCH structure for returns in both periods.

The descriptive statistics related to trading volume changes in Table 3 show that the average trading volume changes for all cryptocurrencies during the pandemic is less than the pre-pandemic period, while the standard deviation of changes in trading volume is higher during the pandemic. The evidence from values in Table 3, does not confirm any significant skewness in trading volume change series in prior and during pandemic periods.

To test the equality of returns’ means, variances, and distributions in pre-COVID-19 and during COVID-19 pandemic, several statistical tests are performed and the results are shown in Table 4. It is evident that mean returns of all markets in pre-COVID-19 period are not significantly different than the means during COVID-19 pandemic. However, except for Bitcoin Cash, EOS, and Chainlink, the variances of other markets are significantly different between the two periods. The Kolmogorov-
Fig. 1. Market volatilities in pre-COVID-19 and during COVID-19 pandemic periods.
Smirnov test [13] examines whether the return distributions in prior and during the COVID-19 pandemic are statistically different and the results show that only the return distributions of Tether, Ethereum, Monero, Gold, WTI, and BRENT are statistically different between two periods.

Likewise, the results of statistical tests to compare the markets’ volatilities in prior and during COVID-19 periods are presented in Table 4. These results show that except for Chainlink and WTI, the average volatility of all markets differs significantly between two periods, while the volatility distribution of all assets differs significantly in these two periods.

Fig. 1 shows the volatility of all thirteen markets before and during pandemic. As displayed, there is a large jump in the volatility of all markets in March 2020 due to the market crash resulting from COVID-19 pandemic declaration by WHO. Moreover, on April 20, 2020, the May 2020 contract futures price for WTI plunged to around -$37 a barrel which caused another leap in volatility. The scale of the volatilities in 2020 is much higher than 2019 and in the following section, the effect of these volatilities on market returns will be investigated.

In order to find any linear association between the return and volume changes, Pearson correlation analysis is performed for each cryptocurrency and the results can be found in Table 5. Before the COVID-19 pandemic all cryptocurrencies, except for Tether, show a significant correlation between the return and changes in trading volume at 5% significance level, while during the pandemic Tether, EOS, and Monero do not support a significant correlation. Thus, existence of a causal relationship between return and trading volume changes for Tether, EOS, and Monero is unlikely during the pandemic.

### Table 5
Pearson correlation between returns and volume changes.

|                     | Pre-COVID-19 (2019) | During COVID-19 (2020) |
|---------------------|---------------------|------------------------|
|                     | Correlation | Probability | Correlation | Probability |
| Tether              | 0.007        | 0.8929       | 0.000        | 0.9988       |
| Bitcoin             | 0.212       | 0.0001       | 0.141       | 0.0072       |
| Ethereum            | 0.195       | 0.0002       | 0.124       | 0.0180       |
| Ripple              | 0.164       | 0.0017       | 0.135       | 0.0098       |
| Litecoin            | 0.360       | 0.0001       | 0.198       | 0.0001       |
| Bitcoin Cash        | 0.284       | 0.0001       | 0.200       | 0.0001       |
| EOS                 | 0.124       | 0.0177       | 0.058       | 0.2639       |
| Chainlink           | 0.465       | 0.0001       | 0.185       | 0.0004       |
| Cardano             | 0.217       | 0.0001       | 0.201       | 0.0001       |
| Monero              | 0.199       | 0.0001       | 0.036       | 0.4871       |

3.2. Return and volatility of return relationships (EGARCH-M)

In this section, the results related to the Return-Volatility relationship are presented. By examining all the return series with Augmented Dickey-Fuller test for stationarity, all return series concluded to be stationary. Referring to the kurtosis and skewness of the return distributions from Table 2, the GARCH effect might be present for the volatility of returns. The Jarque-Bera test [45] for normality is performed on return series to find the existence of GARCH effects and as this test results in Table 6 show, the GARCH structure is available for all thirteen markets in both prior and during COVID-19 pandemic.

The structure of ARMA models for each market in pre-pandemic and during-pandemic are determined by Ljung-Box Q-test for autocorrelations and the AIC method. Then, an EGARCH-M model is applied to return series for investigating the effect of the pandemic on the return-volatility relationship.

Table 7 shows the amount and the direction for the effect of volatilities on cryptocurrencies, Gold, WTI, and BRENT crude oil returns in both pre-COVID-19 and during COVID-19 periods. The EGARCH-M effects are examined with three assumptions for the error distributions: Normal distribution, t-Student distribution, and Generalized Error distribution (GED).

Regarding the effect of COVID-19 on commodity markets such as gold, WTI, and BRENT crude oil, it can be concluded that the gold market was a less volatile asset and the effect of volatility on gold return is not significant in both periods of prior and during the COVID-19 pandemic. Therefore, gold can be considered a suitable asset for portfolio hedging in the periods studied in this paper. The return-volatility relationship for WTI and BRENT crude oil seems to be significant prior to the COVID-19 pandemic and the volatilities in these markets have decreased their returns in this period. However, it can be inferred from Table 7 that the return-volatility relationship for these oil markets during COVID-19 pandemic is not significant.

Table 6 shows boxplots of the probabilities for the significance of EGARCH-M parameter across...
prior and during the COVID-19 periods and Table 8 summarizes the statistics related to this significance. It can be concluded that in cryptocurrency markets, the mean probability of EGARCH-M parameter only differs between two periods of prior and during the COVID-19 under the GED distribution assumption.

### Table 8: EGARCH in mean effects with three different residual distribution assumptions.

| Market | Pre-COVID-19 | During COVID-19 |
|--------|--------------|-----------------|
|        | Normal       | t-Student       | GED             | Normal       | t-Student       | GED             |
| Tether | 0.1818 (0.46)| −0.0185 (0.92) | −0.0150 (0.94) | −0.0504 (0.54)| −0.0445* (0.06)| −0.0792 (0.016)|
| Bitcoin| 0.0295 (0.27)| 0.0310 (0.25)   | 0.0102 (0.51)  | 0.0253 (0.38) | 0.0130 (0.45)  | −0.0022 (0.88) |
| Ethereum| 0.0115 (0.84)| 0.9684 (0.88)  | −0.3721 (0.44) | 0.0079 (0.75) | −0.1122 (0.54) | 0.1160 (0.00)  |
| Ripple | 0.0175 (0.56)| −0.0073 (0.49) | 0.0162 (0.20)  | −0.0036 (0.68) | −0.0050 (0.44) | −0.0136 (0.03) |
| Litecoin| −0.0140 (0.83)| 0.3650 (0.34)  | 0.0355 (0.23)  | −0.0081 (0.37) | 0.0100 (0.47)  | 0.023 (0.11)   |
| Bitcoin Cash| 0.0770 (0.47)| 0.1809 (0.64)  | 0.1368* (0.08) | −0.1047 (0.015)| 0.0059 (0.61)  | 0.036 (0.020)  |
| EOS    | 0.0268 (0.72)| 0.0435 (0.69)  | 0.4931 (0.62)  | 0.0705 (0.52)  | 0.0000 (0.96)  | 0.0272 (0.002) |
| Chainlink| 0.0284 (0.45)| 0.0113 (0.45)  | 0.0094 (0.48)  | 0.0066 (0.96)  | 0.0134 (0.46)  | −0.7572 (0.24) |
| Cardano| 0.0360 (0.37)| 0.0508 (0.13)  | 0.0538 (0.13)  | 0.0177 (0.54)  | 0.3054 (0.11)  | 0.0920 (0.12)  |
| Monero | −0.0056 (0.81)| −0.0044 (0.85) | 0.0075 (0.75)  | 0.0196 (0.44)  | 0.0585 (0.53)  | 0.8008 (0.001) |
| GOLD  | −0.1281 (0.11)| −0.3429 (0.24) | −0.4773 (0.17) | −0.0412 (0.63) | −0.0621 (0.36) | −0.0532 (0.42) |
| WTI   | −0.7605 (0.00)| −4.311 (0.00)  | −1.492 (0.12)  | 0.0000 (0.59)  | 0.0019 (0.45)  | 0.0022 (0.14)  |
| BRENT | 0.0772 (0.41)| −0.2590 (0.0003)| −0.3902 (0.0002)| −0.0059 (0.14) | 0.0072 (0.32)  | 0.0036 (0.62)  |

This table presents the value of $\lambda$ from Eq. (3). Values in the parentheses are associated probabilities. Significant coefficients at 5% level are in bold. Values with (*) are significant at 10% level.

### 3.3. Return and volume change relationships based on Granger causality test

In this section, the unidirectional Granger causality from returns to volume changes, and from volume changes to returns are examined for all cryptocurrencies. To verify the stationarity of time-series before
applying the VAR model and Granger causality tests, ADF unit root test is applied to return and trading volume change time-series. As presented in Table 6, the null hypothesis of having a unit root in ADF test for all returns and volume change time-series is rejected at 1% significant level and the stationarity of these time series is confirmed.

Results from Table 9 show that in pre-COVID-19 pandemic period, only the returns of Chainlink and Monero Granger cause their own volume changes, while during the COVID-19 pandemic, there is a significant Granger causality relationship at 5% level from return to volume changes for Tether, Ethereum, Ripple, Litecoin, EOS, and Cardano. However, there is no significant causal relationship from return to volume changes in Bitcoin, Bitcoin Cash, Chainlink, and Monero cryptocurrencies during the COVID-19 pandemic.

Similarly, the Granger causal relationship from volume changes to the return of each cryptocurrency is investigated. The results confirm that only Litecoin's volume change Granger causes its return prior to the COVID-19 pandemic, while during this pandemic the Granger causality relations from volume changes to returns are only presented in Tether and Chainlink. Our analyses could not find any return-volume relationships prior or during the COVID-19 pandemic in either direction for Bitcoin, or Bitcoin cash at 5% significance level.

The distribution of probabilities for the bidirectional and unidirectional Granger causality tests are presented in Fig. 3. The box plots show larger ranges for the probability of Granger causality tests in all directions during COVID-19 pandemic compared to the pre-COVID-19 period. It is evident that the median probability of Granger causality test from return to volume changes during COVID-19 pandemic is significant, therefore, it can be inferred that most of the cryptocurrencies studied in this paper show Granger causality relationship from return to volume changes during the COVID-19 pandemic.

However, when we consider testing the relationship between volume changes and absolute value of returns, as presented in Table 10, besides for the Monero and Tether, a significant effect from absolute returns towards the volume changes of all cryptocurrencies is found for both periods of prior and during COVID-19 pandemic. However, the causality relationship from volume changes to the absolute returns is only evident for Bitcoin in pre-COVID-19 period and for Litecoin during the COVID-19 period. These results comply with the sequential arrival of information theory confirming that as the price values change more extremely, more investors will buy or sell their cryptocurrency assets.

To further investigate the return-volume relationships for the cryptocurrency market in general, Student t-tests are applied to the sample of resulting probabilities from Granger causality tests. Table 11 shows the associated probabilities for testing the significance of bidirectional and unidirectional relationships between cryptocurrency returns and their trading volume changes for both pre-COVID-19 and during COVID-19 periods.

As indicated in Table 11, the mean of probabilities for bidirectional Granger causality tests between return or absolute returns and volume changes for all ten cryptocurrencies is significant at 1% level, hence the bidirectional return (absolute return)-volume relationship in cryptocurrency markets before and during COVID-19 pandemic is not supported. Similarly, these test results do not confirm any Granger causality relationship from cryptocurrencies' trading volume changes to their returns (absolute returns). However, in both pre-COVID19 and during COVID-19 periods, the mean of probabilities for unidirectional Granger causality tests from returns to volume changes of all ten cryptocurrencies is not significantly different than zero at 1% level. Besides, the mean of probabilities for unidirectional Granger causality tests from absolute returns to volume changes of all ten cryptocurrencies is not significantly different than zero at 5% level. This denotes the existence of causality relation from cryptocurrencies returns (absolute returns) to volume changes for both periods.

In short, our empirical findings are summarized as follow:

1. There is no significant return-volatility relationship in any of cryptocurrencies prior to the COVID-19 pandemic. While this relationship is significant for Tether, Ethereum, Ripple, Bitcoin Cash, EOS, and Monero during COVID-19, there is no significant return-volatility relationship for Bitcoin, Litecoin, Chainlink, and Cardano in this period.
2. The effect of volatility on return for Tether and Ripple is negative, while this relationship is positive for Ethereum, Bitcoin Cash, EOS, and Monero during COVID-19 pandemic.
3. The gold market is less volatile in both periods and the effect of volatility on gold return is not significant prior and during COVID-19 pandemic. Hence, gold can be considered a suitable asset for portfolio hedging in the periods studied in this paper.
4. The effect of volatility on return for WTI and Brent crude oil is significantly negative prior to the COVID-19 pandemic. However, the return-volatility relationships for these oil markets are not significant during pandemic.
5. There is a significant Granger causal relation from return to trading volume changes for Ethereum, Chainlink and Monero in the pre-COVID-19 period and for Ethereum, Ripple, Litecoin, EOS, and Cardano during the COVID-19 period.

### Table 8

Summary statistics of the significance of EGARCH-M parameter.

| Distribution | Mean Pre-Pandemic | Mean During Pandemic | Std. dev. Pre-Pandemic | Std. dev. During Pandemic | Median Pre-Pandemic | Median During Pandemic | Min Pre-Pandemic | Min During Pandemic | Max Pre-Pandemic | Max During Pandemic | Significance of equality of meansa |
|--------------|------------------|----------------------|-------------------------|---------------------------|---------------------|------------------------|-----------------|---------------------|-----------------|---------------------|-------------------------------|
| Normal       | 0.578            | 0.519                | 0.207                   | 0.253                     | 0.515               | 0.530                  | 0.270           | 0.015               | 0.840           | 0.960               | 0.5787                         |
| r-Student    | 0.564            | 0.463                | 0.276                   | 0.271                     | 0.565               | 0.465                  | 0.130           | 0.06                | 0.920           | 0.960               | 0.4032                         |
| GED          | 0.438            | 0.142                | 0.281                   | 0.271                     | 0.460               | 0.025                  | 0.080           | 0.000               | 0.940           | 0.880               | 0.0275                         |

a Values are the probabilities for the null hypothesis of mean p-values for the significance of EGARCH-M parameter in prior and during the COVID-19 periods are equal. Significant values are in bold.

### Table 9

Probability of Granger Causality test.

| H0: Changes in cryptocurrency price (Return) Granger causes changes in the volume During COVID-19 | H1: Changes in the cryptocurrency volume Granger cause changes in the price (return) During COVID-19 |
|---------------------------------------------------------------|---------------------------------------------------------------|
| Tether 0.9478 (2019)                                           | 0.0005 (2020)                                                 |
| Bitcoin 0.8186 (2019)                                         | 0.3675 (2020)                                                 |
| Ethereum 0.0052 (2019)                                        | 0.083 (2020)                                                  |
| Ripple 0.1246 (2019)                                          | 0.0272 (2020)                                                 |
| Litecoin 0.2531 (2019)                                        | 0.0005 (2020)                                                 |
| Bitcoin 0.2561 (2019)                                        | 0.4694 (2020)                                                 |
| Cash 0.3051 (2019)                                            | 0.0033 (2020)                                                 |
| EOS 0.008 (2019)                                              | 0.293 (2020)                                                  |
| Chainlink 0.0093 (2019)                                       | 0.0007 (2020)                                                 |
| Cardano 0.0155 (2019)                                         | 0.0966 (2020)                                                 |

Values in bold are significant at 5% level of significance and values with (*) are significant at 10% level of significance.
6. Except for Litecoin, there is no significant evidence of causal relations from trading volume changes to the return of cryptocurrencies prior to the COVID-19. However, trading volume changes of Tether and Chainlink Granger cause their returns during the COVID-19 period. In general, these results are consistent with prior studies about stock markets such as [32,46] stating that trading volume cannot forecast the return.

7. There is a significant causal relationship from the absolute values of cryptocurrencies returns to the changes in their volume in both periods of prior and during COVID-19 pandemic. This implies that cryptocurrency traders tend to trade in high volumes while prices change extremely and this behavior is not significantly affected by the COVID-19 crisis.

### Table 10

| Cryptocurrency | Pre-COVID-19 | During COVID-19 | Pre-COVID-19 | During COVID-19 |
|----------------|--------------|-----------------|--------------|-----------------|
| Tether         | 0.2068       | 0.0044          | 0.2262       | 0.1372          |
| Bitcoin        | 0.0491       | 0.0086          | 0.0228       | 0.4515          |
| Ethereum       | 0.0013       | 0.0038          | 0.1625       | 0.0563*         |
| Ripple         | 0.0004       | 0.0000          | 0.6997       | 0.7871          |
| Litecoin       | 0.0033       | 0.0006          | 0.7548       | 0.0141          |
| Bitcoin Cash   | 0.0008       | 0.0274          | 0.1916       | 0.5929          |
| EOS            | 0.0002       | 0.0001          | 0.2654       | 0.0868*         |
| Chainlink      | 0.0223       | 0.0000          | 0.2299       | 0.1365          |
| Cardano        | 0.0202       | 0.0001          | 0.2024       | 0.3196          |
| Monero         | 0.6797       | 0.5347          | 0.3831       | 0.5219          |

Values in bold are significant at 5% level of significance and values with (*) are significant at 10% level of significance.
suggests that the return-volatility relationships for Tether, Ethereum, Ripple, Bitcoin Cash, EOS, and Monero are significant during COVID-19 pandemic, while the same relationship is not significant prior to the pandemic for any of the studied cryptocurrencies. Moreover, it is concluded that the COVID-19 pandemic does not play an essential role in the relationship between returns and volatilities of GOLD, WTI, and BRENT crude oil markets.

Our findings about the return-volume relationship support the availability of causal relations from return to trading volume changes for Chainlink and Monero in the pre-COVID-19 period and for Ethereum, Ripple, Litecoin, EOS, and Cardano during the COVID-19 period. Except for Litecoin, there is no significant evidence of causal relations from trading volume changes to the return of cryptocurrencies prior to the COVID-19, while during the COVID-19 period trading volume of Tether and Chainlink Granger cause their returns. The results from most of the studied cryptocurrencies are consistent with [32,46] and the findings about the return-volume relationship for Tether, Ethereum, Ripple, Bitcoin Cash, EOS, and Monero are significant during COVID-19 pandemic, while the same relationship is not significant prior to the pandemic for any of the studied cryptocurrencies. Moreover, it is concluded that the COVID-19 pandemic does not play an essential role in the relationship between returns and volatilities of GOLD, WTI, and BRENT crude oil markets.

Our findings about the return-volume relationship support the availability of causal relations from return to trading volume changes for Chainlink and Monero in the pre-COVID-19 period and for Ethereum, Ripple, Litecoin, EOS, and Cardano during the COVID-19 period. Except for Litecoin, there is no significant evidence of causal relations from trading volume changes to the return of cryptocurrencies prior to the COVID-19, while during the COVID-19 period trading volume of Tether and Chainlink Granger cause their returns. The results from most of the studied cryptocurrencies are consistent with [32,46] and the efficient markets hypothesis [34], which argues that returns should not be predicted by publicly available information, like trading volume.

As a further investigation, the general return-volume relation for cryptocurrency markets is tested and the results show no significant relationship. However, considering the absolute values of returns, we found a significant relationship from cryptocurrencies absolute returns to trading volume changes for both the prior and during COVID-19 periods.

Our analysis has a number of implications for policymakers. Even though cryptocurrencies are not effectively backed by all governments yet, understanding the effect of financial crisis such as the one followed by the advent of COVID-19 on these markets enables policymakers to better react to the dynamics of digital currencies and their potential effects on other financial and commodity markets and adjust their monetary policy decisions. It will give some insights to investors for distinguishing the associated risk with cryptocurrencies and commodity markets and will enable them to decide their positions during the COVID-19 pandemic. In this regard, gold can be considered a suitable asset for portfolio hedging during the pandemic period. Besides, it was found that cryptocurrency traders tend to trade in high volumes while prices change extremely and this behavior is not significantly affected by the COVID-19 crisis. Our findings about the trading volume can help traders and investors identify the effect of momentum and potential trend in cryptocurrencies on their investments.

Table 11
Statistical t-tests for the causality between cryptocurrency returns or absolute returns and changes in volume.

|                      | Pre-pandemic (2019) | p-value | During pandemic (2020) | p-value |
|----------------------|---------------------|---------|------------------------|---------|
| H0: The mean of probabilities for bidirectional granger causality tests between return and change in volume = 0 | 0.0002 | H0: The mean of probabilities for bidirectional granger causality tests between returns and volume changes = 0 | 0.0004 |
| H0: The mean of probabilities for unidirectional granger causality from returns to changes in volume = 0 | 0.0301* | H0: The mean of probabilities for unidirectional granger causality from return to volume changes = 0 | 0.0448* |
| H0: The mean of probabilities for unidirectional granger causality from changes in volume to returns = 0 | 0.0028 | H0: The mean of probabilities for unidirectional granger causality from changes in volume to absolute returns = 0 | 0.0040 |
| H0: The mean of probabilities for bidirectional granger causality tests between absolute return and volume changes = 0 | 0.0179 | H0: The mean of probabilities for bidirectional granger causality between absolute returns and volume changes = 0 | 0.00328 |
| H0: The mean of probabilities for unidirectional granger causality from absolute returns to volume changes = 0 | 0.0023 | H0: The mean of probabilities for unidirectional granger causality from absolute returns to volume changes = 0 | 0.00596 |

* The null hypothesis is not rejected at 1 % significant level. The null hypothesis is not rejected at 5 % significant level for values in bold.

Data availability
Data will be made available on request.

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

Acknowledgments
The authors gratefully acknowledge the financial support of the Chaire Fintech AMF - Finance Montréal, Canada. Contract number 0007.

References
[1] Neslihanoglu S. Linearity extensions of the market model: a case of the top 10 cryptocurrency prices during the pre-COVID-19 and COVID-19 periods. Finanzchnov. 2021;7:38.
[2] Sharif A, Alou C, Yarowaya L. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach. Int Rev Financ Anal. 2020;70:101496.
[3] Chaudhary M, Sodani PR, Das S. Effect of COVID-19 on economy in India: some reflections for policy and programme. J Health Manag. 2020;22:169–80.
[4] Ozili P. Spillover of COVID-19: impact on the global economy. SSRN Electron J. 2020. doi:10.2139/ssrn.3562570.
[5] Senol Z, Zeren F. Coronavirus (COVID-19) and stock markets: the effects of the pandemic on the global economy. EurasJResSocEcon. 2020;7:146–62.
[6] Naeem MA, Bouri E, Peng Z, Shahzad SJH, Vo XV. Asymmetric efficiency of cryptocurrencies during COVID19. Physica A. 2021;565:125562.
[7] Sarkodie SA, Ahmed MT, Owusu PA. COVID-19 pandemic improves market signals of cryptocurrencies—evidence from Bitcoin, Bitcoin Cash, Ethereum, and Litecoin. Financ Res Lett. 2022;44:102049.
[8] Mariana CD, Ekaputra IA, HusodoZA. Are Bitcoin and Ethereum safe-havens for stocks during the COVID-19 pandemic? Financ Res Lett. 2021;38:101798.
[9] Melki A, Nefzi N. Tracking safe haven properties of cryptocurrencies during the COVID-19 pandemic: a smooth transition approach. Financ Res Lett. 2021;102243.
[10] Corbet S, Hou Y, Hu Y, Larkin C, Lucey B, O’Leary L. Cryptocurrency liquidity and volatility interrelationships during the COVID-19 pandemic. Financ Res Lett. 2022;45:102137.
[11] ben Khelifa S, Guessmi K, Urom C. Exploring the relationship between cryptocurrencies and hedge funds during COVID-19 crisis. IntRevFinanceAnal. 2021;76:101777.
[12] Sahoo PK. Cryptocurrency and cryptocurrency markets: an empirical analysis from a linear and nonlinear causal relationship. Stud Econ Financ. 2021;38:454–68.
[13] Demir E, Bilgin MH, Karabulut G, Doker AC. The relationship between cryptocurrencies and COVID-19 pandemic. Eurasian Econ Rev. 2020;10:349–60.
[14] Lahmiri S, Bekiros S. The effect of COVID-19 on long memory in returns and volatility of cryptocurrency and stock markets. Chaos, Solitons Fractals. 2021;151:111221.
[15] Black F. Studies of stock market volatility changes. Proceedings of the Business and Economics Section of the American Statistical Association; 1976. p. 177–81.
[16] Caporale GM, Spagnolo F, Spagnolo N. Macro news and stock returns in the Euro area: a VAR-GARCH-in-mean analysis. Int Rev Financ Anal. 2016;45:180–8.

CRediT authorship contribution statement
The authors declare that the study was realized in collaboration with the same responsibility. All authors read and approved the final manuscript.
[17] Christie AA. The stochastic behavior of common stock variances value, leverage and interest rate effects. J Financ Econ. 1982;10:407–32.

[18] Whaley RE. The investor fear gauge. JPortfolio Manag. 2000;26:12–7.

[19] Lahmiri S, Bekiros S. The impact of COVID-19 pandemic upon stability and sequential irregularity of equity and cryptocurrency markets. Chaos, SolitonsFractals. 2020;138:109936.

[20] Yousef Khan S, Amir A, Khwoja A, Khdawi OK, Gheblehzadeh M. Impact of COVID-19 on price volatility of cryptocurrency. IntJManag. 2021;12:193–205.

[21] López-Cabarcos MA, Pérez-Pico AM, Piñeiro-Chousa J, Šević A. Bitcoin volatility, stock market and investor sentiment. Are they connected? Financ Res Lett. 2021;38:101399.

[22] Kumar AS, Anandarao S. Volatility spillover in crypto-currency markets: some evidences from GARCH and wavelet analysis. Physica A. 2019;524:448–58.

[23] Salisu AA, Ogbonna AE. The return volatility of cryptocurrencies during the COVID-19 pandemic: assessing the news effect. Glob Financ J. 2021;100641.

[24] Karpoff JM. The relation between price changes and trading volume: a survey. JFinancQuantAnal. 1987;22:109–26.

[25] Hou K, Xiong W, Peng L. A tale of two anomalies: the implications of investor attention for price and earnings momentum. SSRN Electron J. 2009. https://doi.org/10.2139/ssrn.976394.

[26] Statman M, Thorley S, Vorkink K. Investor overconfidence and trading volume. RevFinanc Stud. 2006;19:1531–65.

[27] Liu W. A liquidity-augmented capital asset pricing model. J Financ Econ. 2006;82:631–71.

[28] Copeland TE. A model of asset trading under the assumption of sequential information arrival. J Financ. 1976;31:1149–68.

[29] Epps TW, Epps ML. The stochastic dependence of security price changes and transaction volumes: implications for the mixture-of-distributions hypothesis. Econometrica. 1976;44:305–21.

[30] Chen G, Firth M, Rui OM. The dynamic relation between stock returns, trading volume, and volatility. Financ Rev. 2001;36:153–73.

[31] Smirlock M, Starks L. An empirical analysis of the stock price-volume relationship. J Bank Financ. 1988;12:31–41.

[32] Lee BS, Rui OM. The dynamic relationship between stock returns and trading volume: domestic and cross-country evidence. J Bank Financ. 2002;26:51–78.

[33] Behrens J, Schmidt A. Nonlinearity matters: the stock price - trading volume relation revisited. EconModel. 2021;98:371–85.

[34] Fama EF. Efficient capital markets: a review of theory and empirical work. J Financ. 1970;25:383–417.

[35] Leirvik T. Cryptocurrency returns and the volatility of liquidity. Financ Res Lett. 2022;44:162031.

[36] Nelson DB. Conditional heteroskedasticity in asset returns: a new approach. Econometrica. 1991;59:347–70.

[37] Elyasiani E, Mansur I. Sensitivity of the bank stock returns distribution to changes in the level and volatility of interest rate: a GARCH-M model. J Bank Financ. 1998;22:535–63.

[38] Box GEP, Jenkins GM, Reinsel GC, Ljung GM. Time series analysis: forecasting and control. Fifth ed. John Wiley & Sons; 2015.

[39] Ljung GM, Box GEP. On a measure of lack of fit in time series models. Biometrika. 1978;65:297–303.

[40] Akaike H. A new look at the statistical model identification. IEEE TransAutoControl. 1974;19:716–23.

[41] Fisher RA. Theory of statistical estimation. MathProcCambridge PhilosSoc. 1925;22:700–25.

[42] Said SE, Dickey DA. Testing for unit roots in autoregressive-moving average models of unknown order. Biometrika. 1984;71:599–607.

[43] Granger CWJ. Investigating causal relations by econometric models and cross-spectral methods. Econometrica. 1969;37:424–38.

[44] Jarque CM, Bera AK. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. EconLett. 1980;6:255–9.

[45] Ciner C. The stock price-volume linkage on the Toronto stock exchange: before and after automation. RevQuantFinancAccount. 2002;19:335–49.