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Cryptocurrencies and oil price shocks: A NARDL analysis in the COVID-19 pandemic

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ABSTRACT

This study explores potential non-linear and asymmetric interdependencies between oil price shocks and leading cryptocurrency returns. In addition, this research splits changes in crude oil prices into three relevant components: risk, demand, and supply shocks. By applying the NARDL methodology, this paper examines the connection between oil and cryptocurrencies in the period between November 20, 2018 and June 30, 2020, conducting a study of the first wave of the COVID-19 pandemic. Our results confirm that demand shocks show the greatest connection with the returns of the cryptocurrencies analysed. In addition, both short-term and long-term results show a greater interdependence between oil and cryptocurrencies in periods of economic turbulence, such as the SARS-CoV-2 coronavirus crisis.

1. Introduction

The concept of cryptocurrency dates to 1998, although the first cryptocurrency - Bitcoin - was not created until 2009, because of the 2008 global financial crisis. Since that time, the cryptocurrency market has experienced significant growth in recent years, demonstrating its importance and interest in study. Moreover, since the creation of Bitcoin, numerous cryptocurrencies have emerged, reaching a total of 8200 digital assets as of January 7, 2021, as reflected on the coinmarketcap website. According to data from the same website and for the same date, the total capitalization of the cryptocurrency market has exceeded one trillion dollars ($1,006,761,474,689). Some of the factors that have been essential for the growth of this type of market have been the "fourth industrial revolution", the use of intelligent technologies, as well as the acceptance of cryptocurrencies as a means of payment.

The outbreak of the first devastating wave of the COVID-19 pandemic in early 2020 crudely affected economies around the world and had destabilizing effects on global financial markets. In the cryptocurrency market, March 13, 2020 saw the largest weekly drop in the price of Bitcoin (approximately 36%). The first wave of the pandemic also witnessed an unprecedented scenario where the price of a barrel of WTI crude oil turned negative in April 2020 for the first time in history.

Thus, the energy industry has been one of the industries more severely affected by the pandemic because of restrictions in mobility and the blockade, producing a drastic reduction in the demand for oil and, hence, a sharp fall in oil prices as a result of oversupply. Kalyuzhnova and Lee (2020) discuss the effects of the pandemic crisis on oil demand and its implications for the oil industry. The authors claim that the COVID-19 pandemic has led to a build-up of oil stocks never seen before that will cause devastating effects on oil prices even when demand recovers. On the other hand, they stress that, because of this crisis, currently companies have cut their budgets, underlining the danger of lack of investing in oil projects, which are indispensable to provide production capacity in the next decade. Finally, Kalyuzhnova and Lee (2020) confirm that due to the imbalance that has taken place in the energy markets, the oil industry will suffer consequences beyond the health crisis to which it will have to adapt, with the possibility that future oil demand will be significantly reduced from pre-pandemic predictions. Sharif et al. (2020) further argue that while oil markets may recover through OPEC negotiations, the consequences of the sharp fall in geopolitical risk during the pandemic remain the main concern of policy makers in the short- and long-term.

Undoubtedly, oil price shocks have played a significant role in driving financial markets since the onset of the coronavirus pandemic.
Papers such as Ghazani and Khosravi (2020) and Okorie and Lin (2020) highlight that crude oil is one of the crucial commodity markets worldwide and it serves as an underlying asset in the trading of different financial instruments in global financial markets, playing a key role in most economies. Moreover, over the last few years, it has become evident the growing significance of oil-dependent industries and the increased influence of oil price shocks on the global economy. According to Yin et al. (2021), oil market shocks may appear as a crucial source of uncertainty for the cryptocurrency market, since oil price shocks might produce a risk level similar to macroeconomic news, mainly after the mid-2000s with the financialization of the oil market. In addition, some previous studies claim that changes in oil prices are significantly connected to, among others, inflation, real output, monetary policy, changes in international interest rates, etc., so changes in oil prices may be a key factor in the cryptocurrency uncertainty. Therefore, the study of the oil price variations may be crucial for investors, companies, and resources policy makers, among others, mainly focusing the analysis on the impact of oil price fluctuations on other financial markets, such as the cryptocurrency market.

Thus, the main objective of this research is to analyse the impact produced by the SARS-CoV-2 coronavirus pandemic on the interconnection between changes in the crude oil price and the cryptocurrency market. Specifically, this paper contributes to the existing literature in different respects. First, we apply the NARDL (Nonlinear Autoregressive Distributed Lag) methodology developed by Shin et al. (2014) to study the connectedness between top eleven leading cryptocurrencies and crude oil prices by analysing the correlation, cointegration, long- and short-run asymmetries and the persistence in the separate response of cryptocurrencies returns to positive and negative shocks to crude oil. Arize et al. (2017) and Jareño et al. (2019, 2020) remark that one of the main advantages of the NARDL approach is that it is appropriate for small samples regardless of the integration properties of the variables. Thus, the NARDL method has been employed in a number of recent empirical studies with focus on the cryptocurrency market (Bouri et al., 2018, Demir et al., 2021, González et al., 2020b and González et al., 2021, among others). Second, we analyse the impact of oil price shocks on cryptocurrencies by breaking them down into their three components: risk, demand, and supply shocks, according to Ready (2018). As noted by Umar et al. (2021a), the response of financial variables to oil shocks may differ depending on the source of the oil price changes. Assessing the impact of separate oil shocks is especially relevant during the first wave of the COVID-19 pandemic, when restrictions in mobility and the decrease in the industrial activity caused a significant fall in the demand for oil. Corbet et al. (2020a) further argue oil price shocks as a result of oil-related geopolitical tensions between Saudi Arabia and Russia in early March 2020, which could be captured by the risk component of oil price shocks (Akrâmç, 2020). Therefore, our approach will allow us to ascertain whether demand-side shocks and risk shocks play a major role during the pandemic. Furthermore, accounting for the nature of oil price shocks enables to uncover potential interconnections between cryptocurrencies and crude oil otherwise masked when considering the effect of oil price shocks at the aggregated level. Third, most of the papers devoted to the study of the relationship between the cryptocurrency and alternative financial markets focus solely on Bitcoin, with only a few studies including other leading cryptocurrencies (Conlon et al., 2020; Gonzalez et al., 2021; Goodell and Goutte, 2021; Hsu et al., 2021; Umar et al., 2021c). Thus, we employ eleven relevant cryptocurrencies based on market capitalization along the sample period to explore the presence of heterogeneous sensitivities of cryptocurrencies to oil price shocks and, therefore, whether different cryptocurrencies may play alternative roles in investment strategies. Fourth, the present study differs from most closely related studies (Bouri et al., 2018; Das et al., 2020) in several aspects. On the one hand, Bouri et al. (2018) explore the connection between commodity prices (the aggregate commodity index S&P GSCI and gold prices) and the price of Bitcoin by using the NARDL and the quantiles ARDL methods over the period from July 17, 2010 to February 2, 2017. Thus, unlike Bouri et al. (2018), we consider the impact of crude oil shocks on a broader set of cryptocurrencies. Even though crude oil is the most important constituent of the S&P GSCI (the reference percentage dollar weight of West Texas Intermediate (WTI) crude oil futures contracts in June 2021 was 21.78% according to data from S&P Global), the potential effects of crude oil might be partially eclipsed or hidden by the rest of constituents. On the other hand, Das et al. (2020) analyse the hedging and safe-haven properties of Bitcoin and other alternative assets (gold, the Bloomberg commodity index and the US Dollar) with respect to oil-shocks, which are decomposed into demand- and supply-side shocks and risk shocks, over the period spanning from July 20, 2010 to June 20, 2019. Overall, our study extends the two previous works by considering other popular cryptocurrencies in addition to Bitcoin and by investigating whether diversification benefits can be obtained by combining cryptocurrencies along with oil-related products during episodes of financial turmoil, such as the one triggered by the COVID-19 pandemic.

Two noteworthy findings arise from the empirical analysis of this paper. First, we find that over the investigated period there exists consistent evidence of a significant positive (negative) correlation between demand-side crude oil shocks (risk shocks) and cryptocurrencies. Moreover, our results confirm that the cryptocurrency market is more severely affected by demand and risk shocks to crude oil prices during the COVID-19 period, which is consistent with previous findings showing a greater interconnection among financial markets in times of financial instability (Adeyokya and Oliyide, 2021; Bouri et al., 2021; Ferrer et al., 2018; Guo et al., 2021). Second, the outcomes from the empirical analysis indicate that the response of the cryptocurrency market to crude oil shocks is quite homogeneous across cryptocurrencies and across shock types, although Tether reveals itself as a differentiated cryptocurrency. On the one hand, our results show that Tether co-moves negatively (positively) with demand shocks (risk shocks) to crude oil prices both along the whole sample period and the COVID-19 sub-period. On the other hand, we find that Tether is the cryptocurrency least connected to the three components of oil price shocks, even during the pandemic period, which seems to point out towards potential benefits of including Tether in oil-related portfolios for risk diversification purposes. This finding extends previous results of studies in the field documenting safe haven properties of Tether with respect to equities during the COVID-19 turmoil (Conlon et al., 2020; Goodell and Goutte, 2021).

The present research has been divided into different sections, structured as follows. The second section contains a broad review of the financial literature on the cryptocurrency market. The third section describes the data and the methodology applied; specifically, it specifies the variables selected, the sample period and a brief development of the approach used, as well as the analysis of the main descriptive statistics of the variables. The fourth section deals with the analysis of the empirical estimation results obtained under the Nonlinear Autoregressive Distributed Lag (NARDL) methodology. First, the complete sample period is analysed and, subsequently, to confirm the robustness of the results, the sample period is divided into two sub-periods: the pre-COVID-19 sub-period, and the COVID-19 sub-period, which incorporates the current health crisis. Finally, the fifth section compiles the most relevant conclusions of this analysis.

2. Literature review

The financial literature has seen a growing number of empirical studies in recent years devoted to a detailed analysis of cryptocurrencies. Thus, Corbet et al. (2019) perform a comprehensive review of existing studies in the field, indicating that cryptocurrencies are trusted investment assets with legitimate value that must face charges of potential

1 https://www.spglobal.com/spdj/en/indices/commodities/sp-gsci/#overview.
illicit use and inexperienced exchange systems, among others. In turn, Kyriazis (2019) summarises the most relevant results of previous works on the presence of return and volatility spillovers in the cryptocurrency market.

The empirical evidence on the role of cryptocurrencies as either a diversifier, a hedge or a safe haven reported by financial studies yields mixed results depending on the considered cryptocurrencies, the period under investigation and the asset(s) against which the properties of cryptocurrencies for risk management are examined. Thus, Selmi et al. (2018) compare the role of Bitcoin and gold as a hedge, a safe haven and/or a diversifier under different market conditions and find that Bitcoin would serve as a safe haven during political and economic crisis periods. Klein et al. (2018) agree and call Bitcoin the New Gold. In the same line, Guesmi et al. (2019) point out that portfolios and investment strategies that include gold, oil, stocks, and Bitcoins assume lower risk than those in which only the first three are considered. Canh et al. (2019) study the diversification capacity of leading cryptocurrencies with the largest market capitalization against oil and gold price shocks and conclude that cryptocurrencies have insignificant correlations with economic factors, which limits the diversification ability of financial investors. Bouri et al. (2017a) find that the cryptocurrency does have sufficient capability to hedge against uncertainty in the short term and under extreme market conditions, thus corroborating that uncertainty negatively affects Bitcoin returns. Bouri et al. (2017b) recognise Bitcoin as an efficient diversification instrument during economic crises. Kurka (2019) find a weak correlation between Bitcoin and other asset traditional asset classes, with the sole exception of gold. Contrarily, Smales (2019) argues that there is no connection between Bitcoin returns and other asset classes and that until the cryptocurrency market is consolidated, cryptocurrencies should not be considered a safe haven. Das et al. (2020) conclude that Bitcoin is not the superior asset over others (gold, commodity and US dollar) to hedge oil-related uncertainties and they also state that hedging capacity of different assets is conditional upon the nature of oil risks and market situation. Symitsi and Chalvatzis (2019) find statistically significant diversification benefits from the inclusion of Bitcoin in portfolios in bullish and bearish market conditions. Charfeddine et al. (2020) affirm that the relationship between cryptocurrencies and different asset classes (including crude oil) is particularly sensitive to economic and financial disruptions and conclude that cryptocurrencies can be suitable for diversification, although they are poor hedging instruments in most cases. Jareño et al. (2020) obtain a positive and statistically significant interconnectedness between Bitcoin and gold and assert that Bitcoin could be considered as a safe haven during economic turmoil. Bouri et al. (2018b, 2020) analyse the hedging and safe haven properties of cryptocurrencies against the downside risk of U.S. market equities and find that cryptocurrencies are a valuable digital asset class as well as other heterogeneous results that allow investors to improve their ability to manage cryptocurrency portfolios. Shahzad et al. (2020) argue that gold and Bitcoin have different characteristics in terms of their safe haven and hedging function and that diversification is more stable in gold. Finally, Rehman and Vo (2020) find that copper provides maximum diversification opportunities for investors with all cryptocurrencies in the short-run, while, for medium- and long-term investment periods, precious metals under extreme positive return distributions are not integrated with the extreme negative cryptocurrency returns, thereby implying diversification opportunities for investors.

Since cryptocurrencies are currently considered a relevant asset class, in general, and as a hedging and diversification tool, in particular, it is important to know how cryptocurrencies perform in periods of extreme stress and uncertainty (when the majority of asset prices tend to move in the same direction), such as the one triggered by the COVID-19 pandemic. Gonzalez et al. (2020a) examine the behaviour of three asset portfolios composed of stocks, bonds and a cryptocurrency or gold for a pre-COVID-19 and a COVID-19 sub-period. Thus, although cryptocurrencies manifest the ability to control the risk of well-diversified portfolios, not all of them manage to do so in the sample period. In addition, despite stability properties attributed to gold, it was not able to control risk in the unfolding of the COVID-19 financial crisis. Finally, investors should consider altcoins to achieve more effective diversification despite their lower returns. Shahzad et al. (2021) study the daily return spillover among 18 cryptocurrencies under low and high volatility regimes and find strong spillovers across the cryptocurrency markets in low and high volatility regimes, especially during the COVID-19 outbreak. Yousaf and Ali (2020) examine the return and volatility transmission among the three most popular cryptocurrencies during the pre-COVID-19 and the COVID-19 period and find that volatility transmission is not significant among cryptocurrencies during the pre-COVID-19 period, and thus investors can obtain maximum diversification benefits. However, during the COVID-19 period, they find that the dynamic conditional correlations between all cryptocurrency pairs are higher during the COVID-19 period than during the pre-COVID-19 period. Thus, these results would indicate that hedging effectiveness is higher during the COVID-19 period. Finally, they point out that have important implications for investors regarding portfolio diversification, hedging, forecasting, and risk management. Along these lines, Jóbal et al. (2020) attempt to examine the impact that the COVID-19 pandemic has had on the cryptocurrency market and find that there is an asymmetric relationship between COVID-19 and cryptocurrency returns. Furthermore, they find that most cryptocurrencies had the ability to absorb the negative impacts of COVID-19 and act as a hedging instrument during the period of economic turbulence, including Bitcoin. Yarovaya et al. (2020a) have analysed the herding effect on cryptocurrency markets during the SARS-CoV-2 pandemic and their results show that such an effect remains contingent on bullish or bearish market days but does not strengthen during COVID-19. Yarovaya et al. (2020b) study the unique features of the COVID-19 crisis compared to previous crisis episodes and provide directions for future research. Corbet et al. (2020b) study potential interdependencies between the largest cryptocurrencies and find evidence that relevant cryptocurrencies not only provide diversification benefits for investors but also acted as a safe-haven during this pandemic COVID-19 crisis period, a period characterized by marked financial market stress. However, Corbet et al. (2020c) examine the connection between major Chinese financial markets and Bitcoin during the COVID-19 pandemic and find that, in periods of severe financial and economic disruption, these assets do not act as a hedge or safe-haven, but perhaps rather as amplifiers of contagion. In line with this paper, Conlon and McGee (2020), analyse Bitcoin properties and suggest that Bitcoin does not act as a safe haven as Bitcoin decreases in price in lockstep with the S&P 500 as the COVID-19 crisis develops.

As the time of writing this article, the COVID-19 pandemic is still ongoing, we next briefly summarize the main findings of three papers which cover not only what has been called the first wave of the coronavirus crisis (mainly from March to May 2020), but also the consecutive months where successive waves have been identified. Thus, Umar et al. (2020a) investigate the impact of volatility connectedness among cryptocurrencies and three fiat currencies (the euro, GBP and Chinese yuan) during the first and second waves of the COVID-19 pandemic crisis. In this regard, Umar et al. (2021b) report minor differences in terms of the total net return and volatility connectedness of the two types of currencies between the first and second waves, although a stronger pairwise volatility connectedness between cryptocurrencies and fiat currencies is observed during the first wave of the pandemic in comparison to the period...
associated to the second wave. Karamti and Bellhassine (2021) examine the presence of financial contagion among fear linked to COVID-19 in the US stock markets (as proxied by the Infectious Disease Equity Market Volatility index developed by Baker et al., 2020) and international markets based on wavelet coherence analysis during the first and second waves of the pandemic in the US. With respect to the cryptocurrency market, the results in Karamti and Bellhassine (2021) reveal a strong positive correlation between US COVID-19 fear and Bitcoin during the first wave of the pandemic, whereas the fear index clearly leads the Bitcoin market at the start of the second wave, which highlights the role of the cryptocurrency as a safe haven when fear increases. Finally, Goodell and Goutte (2021) employ wavelet coherence and neural network analyses to examine the co-movements between cryptocurrencies and equity indices over the period from February 2019 to February 2021, thus extending deeper into the pandemic crisis than most prior studies. Interestingly, the study of Goodell and Goutte (2021) shows that contagion between Tether and the S&P 500 consistently spikes during periods associated to waves of COVID-19 (i.e., February to April 2020; July to August 2020; November to December 2020; and February 2021). The authors further claim the role of Tether as a diversifier and safe haven during episodes of increased financial instability, such as the more severe stages of the COVID-19 pandemic.

Previous literature analysing the relationship among cryptocurrencies, as well as between cryptocurrencies and other asset classes follows different methodologic approaches, such as VAR models (Baçao et al., 2018 and Conlon and McGee, 2020), GARCH models (Corbet et al., 2020b), VAR-GARCH models (Symisi and Chalvatzi, 2019), bivariate Diagonal BEKK model (Katsiampa, 2019; Katsiampa et al., 2019), BEKK-GARCH models (Beneki et al., 2019; Klein et al., 2018), BEKK-MGARCH models (Tu and Xue, 2019), GARCH-MIDAS model (Walther et al., 2019), DCC models (Charfeddine et al., 2020 and Kumar and Anandarao, 2019), DCC-MGARCH models (Canh et al., 2019), VARMA-DCC-GARCH models (Guesmi et al., 2019), Multivariate factor stochastic volatility models (MFSVM) (Shi et al., 2020), wavelet-based models (Kumar and Ajaz, 2019; Omane-Adjepong and Alagidede, 2019; Mensi et al., 2019; Sharif et al., 2020), Diebold and Yilmaz (2009) approach (Koutmos, 2018), the Quantile Regression approach (Jareño et al., 2020), Quantile cross-spectral approach (Rehman and Vo, 2020), ARDL models (Giaian et al., 2018; Nguyen et al., 2019) and NARDL models (Bouri et al., 2018; Demir et al., 2021; González et al., 2020b). This paper aims to analyse the interdependencies between major cryptocurrencies and oil price shocks by applying the NARDL approach to simultaneously capture long- and short-run asymmetric interdependencies between these variables in a sample period that includes the devastating first wave of the COVID-19 pandemic.

3. Data and methodology

3.1. Data

The aim of this research is to analyse the consequences caused by the advent of COVID-19 on the existing connection between oil prices and the cryptocurrency market. To this end, the data set analysed in this paper consists, on the one hand of the daily returns of eleven major cryptocurrencies by market capitalization. The selected cryptocurrencies are Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Bitcoin_cash (BCH), Tether (USDT), Bitcoin_sx (BSV), Litecoin (LTC), EOS, Binance_coin (BNB), Tezos (XTZ) and Cardano (ADA). The data has been extracted from the coingapmarket website and corresponds to the top cryptocurrencies in terms of market capitalization as of June 2020, when the query was conducted. The selection of the top eleven cryptocurrencies shows around 88% of the cryptocurrency market capitalization and Bitcoin represents approximately 65% dominance in this market, as of November 9, 2020.

In addition, data on oil price shocks have been decomposed, by applying the methodology proposed by Ready (2018), into its three factors: risk shock, supply shock and demand shock (Umar et al., 2020). They have been extracted from Thomson Reuters DataStream.

The sample period of the work extends from November 20, 2018 to June 30, 2020, which ultimately yields 396 daily data observations. The starting point of this period is conditioned by the coincidence of data for all variables and the ending point is established just a few days after the loss of validity of Royal Decree 463/2020, March 14, declaring a state of alarm for the management of the health crisis caused by COVID-19, which marked a return to normality after the first devastating wave of the SARS-CoV-2 pandemic. Specifically, in order to analyse the impact of COVID-19 on the interconnection between oil prices and the cryptocurrency market, the whole sample period has been divided into two sub-periods: the pre-COVID-19 sub-period, the stage prior to the arrival of the SARS-CoV-2 Coronavirus, and the COVID-19 sub-period, the second stage characterized by the crisis generated by the first wave of the COVID-19 pandemic.

This section contains an initial and individual analysis of the variables in order to ascertain the behaviour of each one of them. Table 1 compiles the descriptive statistical parameters and unit root tests of the log-returns of the main cryptocurrencies and the oil price shocks divided into their three components: risk shock (RS), demand shock (DS) and supply shock (SS), all for daily frequency data. We can observe that, in general, the mean of all returns is positive and similar, except for Ripple, Bitcoin cash and EOS. As for the standard deviation, it can be said that in none of the cases it reaches high values, the highest value being around 0.1 for the case of Bitcoin sx.

On the side of skewness, we can observe that it is negative in most of the returns so it can be considered that they have a similar behaviour, except in the case of Tether and Bitcoin sx that show a positive sign.

The kurtosis coefficient is a measure of pointing that indicates the degree of concentration of the data around the mean. In this case, all variables show excess kurtosis for daily returns.

The normality analysis measured through the Jarque-Bera (JB) test shows that all the log returns of the main cryptocurrencies reject the null hypothesis, i.e., the variables do not follow a normal distribution (the values are excessively high).

The stationarity of the variables has been examined by means of the classical unit root and stationarity tests, which are as follows: The Augmented Dickey Fuller (ADF) test, the Philips Perron (PP) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The null hypothesis in the two unit-root tests (ADF and PP) is that the variable has a unit root and therefore is not stationary. On the contrary, the KPSS test establishes as null hypothesis that the variable is stationary. The results obtained indicate the stationarity of all the variables.

Regarding the crude oil components: risk shock (RS), demand shock (DS) and supply shock (SS), the mean in all three cases is close to zero, but negative for both demand and supply shocks. The maximum of all variables is a high and positive value, and the minimum of all of them is negative.

As for the standard deviation, contrary to what happened with the logarithmic returns of cryptocurrencies, we can say that it reaches much higher values in all variables. The skewness is positive only in the case of the risk factor, being negative in the demand and supply shocks, reaching a significant value (~1.90) in the latter.

The kurtosis coefficient of the demand and supply shocks is much higher than the value of the risk factor. The Jarque-Bera test shows the non-normality of the variables since it exhibits very high values. Finally, regarding the stationarity of the variables analysed by means of the ADF, PP and KPSS tests, the results indicate, once again, the non-existence of a unit root and, therefore, the stationarity of the variables.

Additionally, Fig. 1 shows the time evolution of the main cryptocurrency returns over the whole sample period, highlighting the first wave of the pandemic with the shaded area. This figure evidences that during the outbreak of the COVID-19 crisis, there was a crash of the cryptocurrency market.

On the other hand, Fig. 2 shows the time evolution of changes in

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the beginning, in the middle and even near the end of the first wave of crude oil prices and indicates that these changes are highly variable at risk, demand and supply shocks (RS, DS and SS). Fig. 2.

Table 1

| Variables           | Mean  | Median | Max.  | Min.  | Std. Dev. | Skewness | Kurtosis | JB stat. | ADF stat. | PP stat. | KPSS stat. |
|---------------------|-------|--------|-------|-------|-----------|----------|----------|----------|-----------|----------|------------|
| Bitcoin             | 0.0017| 0.0014 | 0.2008| -0.4973| 0.0516    | -2.1586  | 25.6136  | 8745.3***| -22.3580***| -22.2652***| 0.0911     |
| Etherum             | 0.0010| -0.0006| 0.2523| -0.5896| 0.0640    | -1.8517  | 22.3404  | 6398.1***| -12.8752***| -23.4340***| 0.0514     |
| Ripple              | -0.0025| -0.0015| 0.2334| -0.4252| 0.0531    | -1.0443  | 14.2093  | 2145.2***| -22.4574***| -22.4961***| 0.0407     |
| Bitcoin_cash        | -0.0008| -0.0017| 0.4179| -0.5977| 0.0806    | -0.9548  | 16.9756  | 3282.9***| -18.8393***| -18.8360***| 0.0672     |
| Teether             | 0.0001| 0.0000 | 0.0181| -0.0151| 0.0031    | 0.9933   | 14.0689  | 2686.7***| -14.7412***| -22.5888***| 0.2644     |
| Bitcoin_xv           | 0.0021| -0.0015| 0.8579| -0.6226| 0.1037    | 2.6570   | 28.9300  | 11559.9***| -21.8388***| -21.7495***| 0.0395     |
| Litecoin             | 0.0004| 0.0004 | 0.2582| -0.4868| 0.0632    | -0.8193  | 13.4274  | 1838.4***| -21.1380***| -21.1353***| 0.1836     |
| EOS                 | -0.0013| 0.0009 | 0.2664| -0.5446| 0.0702    | -1.1775  | 14.0617  | 2110.5***| -21.1870***| -21.1700***| 0.0690     |
| Binance_coin        | 0.0022| 0.0020 | 0.1803| -0.5813| 0.0634    | -2.1027  | 21.3848  | 5868.9***| -21.5723***| -21.5469***| 0.2897     |
| Tezos               | 0.0026| -0.0001| 0.2638| -0.6144| 0.0751    | -1.2622  | 15.0157  | 2467.3***| -12.0984***| -21.1563***| 0.0889     |
| Cardano             | 0.0012| 0.0009 | 0.2235| -0.5361| 0.0667    | -1.4248  | 14.2230  | 2212.2***| -22.0335***| -21.9117***| 0.1187     |
| Risk Shock (RS)     | 0.2531| -0.8988| 39.9042| -21.3079| 8.7379    | 1.4241   | 6.8184   | 374.42***| -21.1514***| -21.1108***| 0.2670     |
| Demand Shock (DS)   | -0.1016| -0.1151| 14.0218| -13.9575| 1.9052    | -0.9007  | 24.4530  | 7647.33***| -19.7483***| -19.7330***| 0.0435     |
| Supply Shock (SS)   | -0.0128| 0.1575 | 24.1785| -39.9501| 4.8886    | -1.8965  | 28.8108  | 9592.1***| -9.3207***  | -9.5448***  | 0.0520     |

Notes: This table collects the main descriptive statistics. The abbreviations are: min (minimum value), max. (maximum value), JB (Jure-Que-ba test for normality). The ADF (Augmented Dickey-Fuller), PP (Phillips-Perron) and KPSS (Kwiatkowski et al.) test of stationarity are reported. We denote *, **, ***, with statistical significance levels of 10%, 5% and 1%, respectively.

3.2. Methodology

In the present research, a combined methodology has been applied to obtain reliable results for estimation purposes. First, the methodology proposed by Ready (2018) to decompose oil price shocks into risk (RS), demand (DS), and supply (SS) shocks will be briefly explained. Finally, an asymmetric nonlinear cointegration method (Nonlinear Autoregressive Distributed Lag, NARDL) will be used to analyse the interconnection between oil price shocks and the returns of major cryptocurrencies.

3.2.1. Methodology proposed by Ready (2018) to decompose oil price shocks

Relying on existing information about asset prices, this methodology facilitates the decomposition of oil price changes into its three components: risk, demand, and supply shock (RS, DS and SS, respectively). Kilian (2009) proposes a methodology that can be applicable to monthly or quarterly frequency shocks. However, Ready (2018) has the advantage of using oil shocks with a daily frequency thus allowing to obtain the dynamicity of asset returns.

In accordance with Ready (2018), several measures will be used that will allow the decomposition of oil price changes into its three components: risk, demand, and supply (RS, DS and SS, respectively). First, an index of oil-producing companies-represented by the Integrated World Oil and Gas Producers Index. Also, changes in the price of oil-represented by monthly oil futures returns at the second closest maturity for the New York Mercantile Exchange- and changes in expected returns will be used. And finally, as a good proxy for changes in risk, the VIX index will be used. Changes in the latter are identified by means of an ARMA (1,1) process and residuals will be used as innovations (Umar et al., 2020).

In this way, we will obtain demand shocks through the contemporaneous regression residuals of the returns of the World Oil Production Index on detrended VIX innovations (risk shocks). The supply shock is collected as the independent part of oil price changes in demand and risk fluctuations.

3.2.2. Non-linear asymmetric cointegration methodology (NARDL)

To achieve the objective proposed in the present research, we will not only work with the approach outlined above, but, in addition, the nonlinear autoregressive distributed lag (NARDL) model developed by Shin et al. (2014) will be used. This is an asymmetric extension of the well-known ARDL model of Pesaran and Shin (1999) and Pesaran et al. (2001).

The financial literature over the years has employed various techniques such as Ordinary Least Squares (OLS), SUR (Seemingly Unrelated
Regression), Quantile Regression (QR), cointegration and Granger causality, among others, to estimate short and long run interactions under the assumption of symmetric relationships. Thus, the previous approaches are limited since they are not able to point out possible asymmetries. Therefore, in this paper we apply the nonlinear ARDL cointegration approach (NARDL) which allows predicting asymmetries in the short and long run.

This methodology is applied to test the possibility that the time series are nonlinearly cointegrated. It also simultaneously tests for short- and long-run nonlinearities through decompositions of the positive and negative partial sums of the regressors. Finally, this approach allows measuring the separate responses to positive and negative shocks of the regressors of the asymmetric dynamic multipliers.

Along these lines, Arize et al. (2017) and Jareño et al. (2019, 2020), among others, indicate that the NARDL approach has some advantages. Specifically, they suggest that one of the main advantages of the NARDL methodology is that it is appropriate for small samples irrespective of the stationary nature of the variables. In addition, it produces short- and long-run coefficient estimates. The NARDL model is characterized by freedom from residual correlation, which means that the model is therefore not prone to omitting lag bias.

Now, we have to keep in mind that for the empirical realization of the NARDL method classical unit root tests (ADF, PP and KPSS) must be performed to find out whether the variable in question is I(0) or I(1), because the existence of the variable I(2) will make the calculated F-statistic that allows testing cointegration null.

The long-run asymmetric regression between the returns of the top eleven cryptocurrencies and oil price shocks is an approach to estimate asymmetric cointegration based on partial-sum decompositions:

$$ R_p = \alpha_0 + \alpha^* RS^*_t + \alpha^- RS^-_t + \epsilon_p $$

$$ \Delta RS = \nu_t $$

$$ R_t = \alpha_0 + \alpha^* DS^+_t + \alpha^- DS^-_t + \epsilon_p $$

$$ \Delta DS = \nu_t $$

$$ R_p = \alpha_0 + \alpha^* SS^+_t + \alpha^- SS^-_t + \epsilon_p $$

$$ \Delta SS = \nu_t $$

where $R_p$, $RS$, $DS$, and $SS$ are scalar I(1) variables. Specifically, $R_p$ are the returns of the top eleven cryptocurrencies corresponding to period $t$, $RS$ is the risk shock for period $t$, which decomposes as $RS_t = RS_{t,}\cdot + RS^{'}_{t,}\cdot$, where $RS^+$ and $RS^-$ are partial sums of positive and negative changes in the risk shocks. $DS$ is the demand shock for period $t$, which decomposes as $DS_t = DS_{t,}\cdot + DS^{'}_{t,}\cdot + DS^{''}_{t,}\cdot$, where $DS^+$ and $DS^-$ are partial sums of positive and negative changes in demand shocks. Similarly, $SS$ is the supply shock for period $t$, which decomposes as $SS_t = SS_{t,}\cdot + SS^{'}_{t,}\cdot + SS^{''}_{t,}\cdot$, where $SS^+$ and $SS^-$ are partial sums of positive and negative changes in supply shocks. $\epsilon_p$ and $\nu_t$ are random shocks and $a = (\alpha_0, \alpha, \alpha^-)$ is a vector of long-run parameters to be estimated. In detail, the coefficients $a^+$ and $a^-$ capture the long-run relationship between the returns of the eleven major cryptocurrencies and increases ($a^+$) or decreases ($a^-$), respectively, in oil price shocks.

$$ RS^*_t = \sum_{i=1}^{m} \Delta RS^*_t = \sum_{i=1}^{m} \min(\Delta RS^*_t, 0) $$

$$ RS^*_t = \sum_{i=1}^{m} \Delta RS^*_t = \sum_{i=1}^{m} \max(\Delta RS^*_t, 0) $$

$$ DS^*_t = \sum_{i=1}^{m} \Delta DS^*_t = \sum_{i=1}^{m} \max(\Delta DS^*_t, 0) $$

Following Pesaran and Shin (1999), Pesaran et al. (2001), Shin et al. (2014) and Jareño et al. (2019), the interconnection between the returns of the cryptocurrencies market can be integrated into a NARDL configuration as follows:

$$ R_p = \beta_0 + \beta_1 R_{t-1} + \beta_2 RS^*_t + \beta_3 RS^-_t + \beta_4 DS^*_t + \beta_5 DS^-_t + \beta_6 SS^*_t + \beta_7 SS^-_t + \beta_8 R_{t-1} + \sum_{i=1}^{p} \phi_i R_{t-i} + \epsilon_p $$

where $\phi_i$ is the autoregressive parameter, $p$ is the number of lags of the dependent variable and $q$ is the number of lags for the regressors, $\gamma_t$ and $\chi_t$ are the asymmetric distributed lag parameters. $\epsilon_p$ is a variable with zero mean and constant variance, $\sigma^2$. $\alpha^+$ and $\alpha^-$ are the coefficients of the impacts of increases and decreases in oil prices respectively on each of the returns of the eleven most popular cryptocurrencies in the long run.

$$ \sum_{i=0}^{p} \gamma_i \text{ and } \sum_{i=0}^{q} \chi_i $$, on the contrary, it measures the short-term effects of increases and decreases (respectively) of oil price changes on the returns of major cryptocurrencies. Therefore, not only the long-term asymmetric relationship is considered, but the short-term asymmetry of oil price changes is also captured.

Finally, the proposed NARDL model will be estimated using stepwise regression through the error correction model (ECM). The latter allows improving the performance of the NARDL model in small samples and increases the power of the cointegration tests.

4. Empirical results

This section shows the results obtained from the estimation performed for the returns of the cryptocurrencies selected in this paper (Bitcoin, Ethereum, Ripple, Bitcoin_cash, Tether, Bitcoin_SV, Litecoin, EOS, Binance_coin, Tezos and Cardano) and the oil price shocks, divided into its three main components (risk shock, demand, and supply).

The estimation of the model has been carried out through the NARDL methodology for a sample period from November 20, 2018 to June 30, 2020. Moreover, to contrast the robustness of the results, this research analyses whether the interconnection between the main variables studied shows a different behaviour according to the stage of the economy through the division of the whole sample period into two sub-periods: prior to the global declaration of the COVID-19 pandemic by the World Health Organization (WHO) on March 11, 2020 and during the health crisis.

4.1. Results of the NARDL model for the whole sample period (November 20, 2018–June 30, 2020)

Tables 2-4 show the results obtained through the regression of the nonlinear ARDL model together with the asymmetry and cointegration tests between the returns of the eleven leading cryptocurrencies (Bitcoin, Ethereum, Ripple, Bitcoin Cash, Tether, Bitcoin SV, Litecoin, EOS,
Table 2
Regression results of non-linear ARDL models and asymmetry and cointegration tests between dominant cryptocurrency returns and changes in oil prices: Risk Shocks (RS) in the whole sample period (November 20, 2018–June 30, 2020).

| Cryptocurrencies | PCorr  | Coint  | Eq     | LAsym | SAsym | Lags $^+$ | Lags $^-$ | Adj. R² |
|------------------|--------|--------|--------|-------|-------|----------|----------|--------|
| Bitcoin          | −0.1287*** | 1.8174 | $e_t^\gamma = -7.66596-05$ | 0.0055 | - | - | - | 0.0366 |
| Etherum          | −0.1819*** | 2.9606** | $e_t^\gamma = -8.13096-05$ | 0.0506 | - | - | - | 0.0783 |
| Ripple           | −0.1803*** | 2.0522 | $e_t^\gamma = -6.73026-05$ | 0.1931 | - | - | - | 0.0444 |
| Bitcoin_cash     | −0.1036**  | 0.5973 | $e_t^\gamma = -0.0005$ | 0.2876 | - | - | - | 0.0187 |
| Tether           | 0.0443    | 1.7609 | $e_t^\gamma = -6.5186-06$ | 1.3497 | - | - | - | 0.0747 |
| Bitcoin_sv       | −0.1695*** | 1.2300 | $e_t^\gamma = 4.4666-04$ | 0.0030 | - | - | - | 0.0312 |
| Litecoin         | −0.1642*** | 0.6986 | $e_t^\gamma = -0.0005$ | 0.4258 | (2): −0.0010*** | - | - | 0.0418 |
| EOS              | −0.1496*** | 0.5713 | $e_t^\gamma = 6.77306-05$ | 0.0066 | - | - | - | 0.0274 |
| Binance_coin     | −0.2279*** | 1.4938 | $e_t^\gamma = -0.0006$ | 0.9098 | (2): −0.0001* | - | - | 0.0727 |
| Tezos            | −0.2581*** | 0.6862 | $e_t^\gamma = 0.0013$ | 0.3021 | - | - | - | 0.1113 |
| Cardano          | −0.2038*** | 2.4268* | $e_t^\gamma = -0.0008$ | 0.7335 | (2): −0.0010* | - | - | 0.0643 |

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency returns and oil price shocks.

PCorr refers to the Pearson’s correlation coefficients defined by the null of PCorr = 0. Coint refers to the Wald test for the presence of cointegration defined by $\beta_1 = \beta_2 = \beta_3 = 0$. Eq shows the cointegration equation (long-run elasticities) between cryptocurrency returns and risk shocks (RS) $R_{ij} = e_t^\gamma + RS_{ij} + e_t^\gamma$. LAsym refers to the Wald test for the null of long-run symmetry defined by $-\beta_2/\beta_1 = -\beta_2/\beta_1$. SAsym refers to the Wald test for the null of short-run symmetry defined by $\gamma_i = \gamma_i$.

Lags $^+$ and Lags $^-$ show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for ()-lags on the rest of relevant cryptocurrencies.

As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.

Table 3
Regression results of non-linear ARDL models and asymmetry and cointegration tests between dominant cryptocurrency returns and changes in oil prices: Demand Shocks (DS) in the whole sample period (November 20, 2018–June 30, 2020).

| Cryptocurrencies | PCorr  | Coint  | Eq     | LAsym | SAsym | Lags $^+$ | Lags $^-$ | Adj. R² |
|------------------|--------|--------|--------|-------|-------|----------|----------|--------|
| Bitcoin          | 0.3079*** | 1.8480 | $e_t^\gamma = 0.0104^*$ | 0.8602 | 7.2251*** | - | (1): −0.0045** | 0.1688 |
| Etherum          | 0.3054*** | 7.8289*** | $e_t^\gamma = 0.0102**$ | 2.0851 | 6.1169** | - | (1): −0.0047** | 0.1823 |
| Ripple           | 0.2717*** | 4.5554*** | $e_t^\gamma = 0.0088***$ | 1.3770 | 6.0443*** | - | (1): −0.0039* | 0.1138 |
| Bitcoin_cash     | 0.2359*** | 1.7619 | $e_t^\gamma = -0.0066$ | 0.0835 | 5.7142** | - | (1): −0.0079** | 0.1159 |
| Tether           | −0.0386 | 2.4112*  | $e_t^\gamma = 2.0432E-04$ | 0.0005 | - | - | (1): −0.0033** | 0.0897 |
| Bitcoin_sv       | 0.1812**  | 2.8624** | $e_t^\gamma = 0.0238**$ | 1.3425 | 3.8253*** | (3): −0.0080 | (3): 0.0080* | 0.0700 |
| Litecoin         | 0.2763**  | 0.8703 | $e_t^\gamma = 0.0163$ | 0.5280 | 6.5658** | - | (3): 0.0049* | 0.1292 |
| EOS              | 0.2501*** | 0.7111 | $e_t^\gamma = 0.0132$ | 0.2259 | 5.9587** | - | (1): −0.0052* | 0.1155 |
| Binance_coin     | 0.2952*** | 1.0128 | $e_t^\gamma = 0.0468$ | 0.1480 | 6.7686** | - | (1): −0.0047* | 0.1482 |
| Tezos            | 0.2945*** | 0.7389 | $e_t^\gamma = -0.0279$ | 0.0602 | 6.3036** | - | (1): −0.0108*** | 0.2107 |
| Cardano          | 0.3043*** | 6.0105*** | $e_t^\gamma = -0.0256$ | 0.3339 | 6.9926** | - | (3): 0.0099*** | 0.1445 |

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency returns and oil price shocks.

PCorr refers to the Pearson’s correlation coefficients defined by the null of PCorr = 0. Coint refers to the Wald test for the presence of cointegration defined by $\beta_1 = \beta_2 = \beta_3 = 0$. Eq shows the cointegration equation (long-run elasticities) between cryptocurrency returns and demand shocks (DS) $R_{ij} = e_t^\gamma + DS_{ij} + e_t^\gamma$. LAsym refers to the Wald test for the null of long-run symmetry defined by $-\beta_2/\beta_1 = -\beta_2/\beta_1$. SAsym refers to the Wald test for the null of short-run symmetry defined by $\gamma_i = \gamma_i$.

Lags $^+$ and Lags $^-$ show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for ()-lags on the rest of relevant cryptocurrencies.

As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.
analysed cryptocurrencies, and finally, column 9 shows the changes (respectively) in oil price shocks for (1
includes the cointegration equation (long-run elasticities) representing price returns (risk, demand, and supply shocks), respectively, for the and column 6 the Wald test for short-run symmetry. Columns 7 and 8 contains the Wald test to assess the presence of cointegration. Column 4 formation about the Pearson correlation coefficient and column 3 con
Binance coin, Tezos and Cardano) and the three components of the oil -
Table 4
Regression results of non-linear ARDL models and asymmetry and cointegration tests between dominant cryptocurrency returns and changes in oil prices: Supply Shocks (SS) in the whole sample period (November 20, 2018–June 30, 2020).

| Cryptocurrencies | PCorr | Coint | Eq | LAsym | SSAsym | Lags + | Lags − | Adj. R² |
|------------------|-------|-------|----|-------|---------|-------|-------|-------|
| Bitcoin          | −0.0052 | 1.8786 | e: 0.0028 | 0.6255 | − | − | (2): −0.0020** | 0.0468 |
| Ethereum         | −0.0123 | 3.8708*** | e: 0.0032** | 0.3235 | − | − | (3): 0.0020** | 0.0687 |
| Ripple           | −0.0321 | 3.4610** | e: 0.0040** | 0.5438 | − | − | (3): 0.0023** | 0.0352 |
| Bitcoin, cash    | 0.0166 | 0.9652 | e: −5.3941E-03 | 2.97E−05 | − | − | (3): 0.0030** | 0.0149 |
| Tether           | −0.0262 | 1.5127 | e: 9.5224E-06 | 0.7888 | − | − | − | 0.0730 |
| Bitcoin, sv      | 0.0351 | 1.3854 | e: 0.0029 | 0.0022 | − | (2): −0.0036* | 0.0345 |
| Litecoin         | −0.0042 | 1.6361 | e: 0.0083* | 0.8000 | − | (3): 0.0021* | 0.0182 |
| EOS              | 0.0021 | 1.1079 | e: 0.0065 | 0.3202 | − | (3): 0.0023** | 0.0147 |
| Binance_coin     | −0.0264 | 2.7419** | e: 0.0076** | 1.5497 | − | (3): 0.0025** | 0.0279 |
| Tezos            | −0.0028 | 0.9373 | e: 0.0126 | 0.2107 | − | (1): 0.0029* | (2): −0.0026* | 0.0805 |
| Cardano          | −0.0183 | 3.8325*** | e: 0.0120 | 0.0063** | 0.0132 | − | (3): 0.0027** | 0.0339 |

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency returns and oil price shocks. **PCorr** refers to the Pearson’s correlation coefficients defined by the null of **PCorr** = 0. **Coint** refers to the Wald test for the presence of cointegration defined by β1 = β2 = β3 = 0. **Eq** shows the cointegration equation (long-run elasticities) between cryptocurrency returns and supply shocks (SS) $H_0: \beta_1 = \beta_2 = \beta_3 = 0$. **SSAsym** refers to the Wald test for the null of long-run symmetry defined by $\beta_2/\beta_1 = \beta_3/\beta_1$. **LAsym** refers to the Wald test for the null of short-run symmetry defined by $\gamma_1 = \gamma_2$. **Lags +** and **Lags −** show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for ()-lags on the rest of relevant cryptocurrencies returns. As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.

Binance coin, Tezos and Cardano) and the three components of the oil price returns (risk, demand, and supply shocks), respectively, for the whole sample period analysed in the present research (from November 20, 2018 to June 30, 2020).

These tables present the following structure. Column 2 presents information about the Pearson correlation coefficient and column 3 contains the Wald test to assess the presence of cointegration. Column 4 includes the cointegration equation (long-run elasticities) representing the equilibrium relationship between oil price changes and cryptocurrency returns, column 5 shows the Wald test for long-run symmetry, and column 6 the Wald test for short-run symmetry. Columns 7 and 8 provide the effect of the cumulative sum of positive and negative changes (respectively) in oil price shocks for (1–4) lags on the set of analysed cryptocurrencies, and finally, column 9 shows the $R^2$ for each cryptocurrency.

First, the Pearson’s correlation coefficients reported in the second column of Tables 2–4 show that the null hypothesis of no correlation ($H_0: \text{PCorr} = 0$) is rejected for all cryptocurrencies except for Tether for risk and demand shocks, while this null hypothesis is not rejected by any cryptocurrency for supply shocks. More precisely, in Table 2, a negative and statistically significant relationship at 1% level can be observed between changes in risk shock and the returns of Bitcoin, Ethereum, Ripple, Bitcoin, sv, Litecoin, EOS, Binance coin, Tezos and Cardano. Only in the case of Bitcoin, cash the statistical significance is 5%. However, in Table 3, a positive correlation of at least 20% can be observed between the demand shock and all cryptocurrency returns (except for Tether) and, moreover, all cryptocurrencies show a high degree of statistical significance with the demand shocks. On the other hand, the results in Table 4 evidence that there is a lower impact of the third oil price component, supply shocks, compared to the other two (risk and demand shocks).

Second, the existence of cointegration is shown in the third column of Tables 2–4, measured through the Wald F test. The null hypothesis of no cointegration ($H_0: \beta_1 = \beta_2 = \beta_3 = 0$) is rejected for two cryptocurrencies, Ethereum and Cardano (Table 2); for five cryptocurrencies, Ethereum, Ripple, Tether, Bitcoin, sv and Cardano (Table 3) and for three cryptocurrencies, Ethereum, Binance coin and Cardano (Table 4) for risk, demand and supply shocks, respectively. These results indicate a long-run connection between changes in risk, demand and supply shocks and those cryptocurrency returns. Furthermore, the long-run coefficients of the three components of oil price changes are positive and statistically significant. Overall, Ethereum and Cardano show cointegration for the three components of oil price (risk, demand and supply shocks) in the full sample period.

Third, the cointegration equation (see equation (13)) between changes in the three components of the oil price and the returns of the eleven cryptocurrencies is reported in the fourth column of Tables 2–4. All cryptocurrency returns respond in the same direction to positive and negative changes in the three components of the oil price returns, except for Tether with respect to the supply shocks. Moreover, all cryptocurrencies show very low coefficients in all three oil price components and in these three cases Tether ranks with the lowest coefficients. The long-run elasticities for the cumulative sum of positive and negative changes in oil price returns are not statistically significant for any cryptocurrency for risk shocks; while these long-run elasticities are positive and statistically significant for six cryptocurrencies (Bitcoin, Ethereum, Ripple, Bitcoin, sv, Binance coin and Cardano) for demand shocks, as well as for five cryptocurrencies (Ethereum, Ripple, Litecoin, Binance coin and Cardano) for supply shocks.

Fourth, the Wald test for examining long-run symmetry is exhibited in the fifth column of Tables 2–4. The results obtained show that the null hypothesis of long-run symmetry ($H_0: \beta_2/\beta_1 = \beta_3/\beta_1$) is not rejected for any of the cryptocurrencies for the three components of the oil price returns. Therefore, the Wald test indicates that there is no evidence of asymmetric responses over the whole sample period of cryptocurrency returns to changes in the risk, demand and supply shocks.

Fifth, the Wald test for short-term symmetry shown in the sixth column of Tables 2–4 indicates that the null hypothesis of short-term
symmetry ($H_0: \gamma_1 = \gamma_2$) is rejected by all cryptocurrencies for demand shocks (Table 3) since all of them show positive and highly significant coefficients at the 1% significance level, and taking into account that for Tether there is no information. Thus, there is strong evidence of asymmetric short-run responses of all cryptocurrency returns to changes in demand shocks, but no evidence of long-run asymmetry. However, there is no short-run symmetry information for risk and supply shocks.

Sixth, the effect of the cumulative sum of positive and negative changes in the three components of oil price returns for 1 to 4 lags on the eleven leading cryptocurrency returns is reported in the seventh and eighth columns of Tables 2-4. There is a negative and statistically significant effect of positive changes in the risk shocks (Table 2) on just three cryptocurrencies (Litecoin, Binance_coin and Cardano) for 2 lags at 1% significance level, while for negative effects no information is available. Moreover, there is a positive and statistically significant effect for the cumulative sum of positive changes in demand shocks (Table 3) for Bitcoin SV returns (for 3 lags), while there is a negative and statistically significant effect of the cumulative sum of negative changes in demand shocks on all the eleven cryptocurrency returns (for 3 lags except Tether for 1 lag); as well as a negative and statistically significant effect of the cumulative sum of negative changes in demand shocks on five out of eleven cryptocurrencies’ returns -Bitcoin, Bitcoin cash, Litecoin, EOS and Binance_coin- (for 1 lag except Litecoin for 4 lags). In addition, there is just a positive and statistically significant effect of the cumulative sum of positive changes in supply shock (Table 4) on Tezos returns (for 1 lag) and two negative and statistically significant effect of the cumulative sum of positive changes in supply shock on Bitcoin SV and Tezos returns (for 2 lags). On the other hand, there is a positive and statistically significant effect of the cumulative sum of negative changes in supply shocks on nine out of eleven cryptocurrencies’ returns -Bitcoin, Ethereum, Ripple, Bitcoin cash, Litecoin, EOS, Binance_coin, Tezos and Cardano- (for 3 lags). There is also a negative and statistically significant effect of the cumulative sum of negative changes in supply shocks on Bitcoin returns (for 2 lags). Overall, there is a high persistence in the effect of just negative changes in demand and supply shocks in most cryptocurrencies returns in the whole sample period.

Finally, the explanatory power of the nonlinear ARDL model is shown in the ninth column of Tables 2–4. The $R^2$ values range from 1.87% (Bitcoin_cash) to 11.13% (Tezos) for risk shocks; from 7% (Bitcoin SV) to 21.07% (Tezos) for demand shocks, and from 1.47% (EOS) to 8.05% (Tezos) for supply shocks in the whole sample period.

4.2. Robustness checks

To ensure the robustness of the model, this section proposes a division of the sample period into two sub-periods: the pre-COVID-19 and the COVID-19 sub-period to analyse the exceptional health crisis situation caused by the SARS-CoV-2 virus in depth.

The pre-COVID-19 sub-period runs from November 20, 2018 to February 28, 2020, which includes the time characterized by the absence of the virus. This first sub-period has been selected to reach the maximum possible extension prior to the appearance of COVID-19 in our country.

The COVID-19 sub-period runs from March 2 to June 30, 2020 to analyse in depth how the crisis caused by this pandemic is affecting the interdependence between oil price shocks and some leading cryptocurrency returns. The beginning of this sub-period is determined by the approximate date on which the first case of Coronavirus was formally detected in Spain, although numerous investigations reveal its presence as early as the end of January and beginning of February. Thus, it is a sub-period that encompasses the well-known first wave of COVID-19, marked by a situation of health, economic and financial crisis.

4.2.1. NARDL model estimation: pre-COVID-19 sub-period (November 20, 2018–February 28, 2020)

Tables 5–7 show the regression results of the non-linear ARDL model and the asymmetry and cointegration tests between the returns of the eleven selected cryptocurrencies (Bitcoin, Ethereum, Ripple, Bitcoin

Table 5

| Cryptocurrencies | PCorr | Coint | Eq | LAsym | SAsym | Lags $^+$ | Lags $^-$ | Adj. $R^2$ |
|------------------|-------|-------|----|-------|--------|-----------|-----------|------------|
| Bitcoin          | 0.0969* | 0.6266 | $e^*: 0.0260$ | 0.0128 | - | - | - | 0.0151 |
| Etherum          | 0.0352 | 0.4142 | $e^*: -5.4713E-04$ | 0.0414 | - | - | - | 0.0282 |
| Ripple           | -0.0100 | 0.1428 | $e^*: -0.0020$ | 0.1130 | - | - | (2): -0.0013* | 0.0179 |
| Bitcoin_cash     | 0.0600 | 2.2091* | $e^*: -5.3745E-04$ | 0.0010 | - | - | - | 0.0201 |
| Tether           | 0.0076 | 1.7083 | $e^*: 0.0002$ | 1.3678 | - | - | - | 0.0794 |
| Bitcoin SV       | -0.0538 | 0.9321 | $e^*: 0.0003$ | 0.1105 | - | - | - | 0.0255 |
| Litecoin         | 0.0235 | 0.4656 | $e^*: 0.0004$ | 0.0631 | (2): -0.0014** | - | - | 0.0217 |
| EOS              | 0.0244 | 0.4727 | $e^*: 0.0124$ | 0.1208 | (1): -0.0012* | (2): -0.0013* | - | 0.0183 |
| Binance coin     | -0.0370 | 0.8903 | $e^*: 0.0024$ | 0.0227 | (2): -0.0014** | - | - | 0.0246 |
| Tezos            | -0.0640 | 0.7200 | $e^*: -0.0039$ | 0.1176 | - | - | - | 0.0493 |
| Cardano          | -0.0186 | 0.0420 | $e^*: -0.0067$ | 0.0072 | - | - | - | 0.0004 |

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency returns and oil price shocks. PCorr refers to the Pearson’s correlation coefficients defined by the null of $PCorr = 0$. Coint refers to the Wald test for the presence of cointegration defined by $\beta_1 = \beta_2 = \beta_3 = 0$. Eq shows the cointegration equation (long-run elasticities) between cryptocurrency returns and risk shocks (RS) $RS_i = e^* \cdot RS_i^e + e^* \cdot RS_i^e \cdot \text{LAsym}$ refers to the Wald test for the null of long-run symmetry defined by $-\beta_3/\beta_1 = -\beta_3/\beta_1$. SAsym refers to the Wald test for the null of short-run symmetry defined by $\gamma_i^+ = \gamma_i^-$. Lags $^+$ and Lags $^-$ show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for ($i$)-lags on the rest of relevant cryptocurrency returns.

As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.
Table 6: Regression results of non-linear ARDL models and asymmetry and cointegration tests between dominant cryptocurrency returns and oil price shocks: Demand Shocks (DS) in the pre-COVID-19 subperiod (November 20, 2018–February 28, 2020).

| Cryptocurrencies | PCorr  | Coint  | Eq  | LAsym | SAsym | Lags L | Lags S | Adj. R² |
|------------------|--------|--------|-----|-------|-------|--------|--------|--------|
| Bitcoin          | 0.1248** | 0.4843 | e**: -0.0833 | 0.0667  | -     | -      | -     | 0.0181 |
| Ethereum         | 0.1265** | 0.8996 | e**: -0.0125 | 0.2322  | -     | (3): 0.0137* | (2): 0.0131** | 0.0816 |
| Ripple           | 0.0800  | 0.7164 | e**: -0.0200 | 0.3902  | -     | (4): -0.0115* | (2): -0.0143*** | 0.0552 |
| Bitcoin_cash     | 0.0676  | 3.0205** | e**: 0.0257* | 1.6573  | -     | (4): -0.0164* | -   | 0.0411 |
| Tether           | 0.0523  | 2.1620* | e**: 0.0010 | 1.6486  | -     | (4): -0.0008** | (2): -0.0010*** | 0.1118 |
| Bitcoin_xv       | 0.0156  | 1.2772 | e**: -0.0522 | 0.9657  | -     | -      | (3): -0.0215** | 0.0396 |
| Litecoin         | 0.0983* | 1.6205 | e**: 0.0348 | 0.3528  | -     | (4): -0.0161** | (2): -0.0153** | 0.0388 |
| EOS              | 0.0694  | 0.8449 | e**: 0.0007 | 0.1353  | -     | -      | (2): -0.0174** | 0.0220 |
| Binance_coin     | 0.0454  | 1.6234 | e**: 0.0256 | 0.1773  | -     | -      | -   | 0.0155 |
| Tezos            | 0.0867  | 2.4193* | e**: 0.1589* | 0.2292  | -     | (1): 0.0271*** | (2): 0.0203*** | 0.1264 |
| Cardano          | 0.0907* | 0.6028 | e*: 0.0311 | 0.8534  | 0.0011 | -      | -     | 0.0165 |

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency returns and oil price shocks. PCorr refers to the Pearson’s correlation coefficients defined by the null of PCorr = 0. Coint refers to the Wald test for the presence of cointegration defined by $\beta_1 = \beta_2 = \beta_3 = 0$. Eq shows the cointegration equation (long-run elasticities) between cryptocurrency returns and demand shocks (DS) $R_{ij} = e^t \cdot DS_{ij} + e^t \cdot DS_{ij}$. LAsym refers to the Wald test for the null of long-run symmetry defined by $-\beta_2/\beta_1 = -\beta_3/\beta_1$. SAsym refers to the Wald test for the null of short-run symmetry defined by $\gamma_1 = \gamma_1$. Lags L and Lags S show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for (1)-lags on the rest of relevant cryptocurrencies returns. As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.

Table 7: Regression results of non-linear ARDL models and asymmetry and cointegration tests between dominant cryptocurrency returns and changes in oil prices: Supply Shocks (SS) in the pre-COVID-19 subperiod (November 20, 2018–February 28, 2020).

| Cryptocurrencies | PCorr  | Coint  | Eq  | LAsym | SAsym | Lags L | Lags S | Adj. R² |
|------------------|--------|--------|-----|-------|-------|--------|--------|--------|
| Bitcoin          | -0.0259 | 0.1168 | e**: -0.4066 | 0.0001  | -     | -      | (2): -0.0035 | 0.0088 |
| Ethereum         | 0.0173  | 0.4779 | e**: 0.0018 | 0.0166  | -     | (2): -0.0059** | 0.0541 |
| Ripple           | -0.0416 | 0.0742 | e**: -0.0076 | 0.0251  | -     | (3): -0.0052* | (2): -0.0047* | 0.0294 |
| Bitcoin_cash     | 0.0153  | 2.1877* | e**: 0.0006 | 0.3790  | -     | -      | 0.0208 |
| Tether           | -0.1075* | 0.9310 | e**: -0.6877=0.05 | 0.7275  | -2.6963*** | -      | -     | 0.0867 |
| Bitcoin_xv       | 0.0533  | 1.0983 | e**: -0.0087 | 0.2836  | -     | (4): -0.0117** | 0.0416 |
| Litecoin         | 0.0038  | 0.9837 | e**: -0.0015 | 0.3181  | -     | (4): -0.0055* | -   | 0.0192 |
| EOS              | 0.0100  | 0.1314 | e**: -6.7251E-03 | 0.0003  | -     | (1): -0.0080** | (1): 0.0078** | 0.0265 |
| Binance_coin     | -0.0468 | 1.5829 | e**: -0.0245 | 0.3011  | -     | (2): -0.0053 | 0.0227 |
| Tezos            | 0.0109  | 0.4798 | e**: 0.0002 | 0.3184  | -     | -      | 0.0471 |
| Cardano          | 0.0157  | 0.3759 | e**: 0.00674 | 0.0005  | -     | -      | 0.0036 |

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency returns and oil price shocks. PCorr refers to the Pearson’s correlation coefficients defined by the null of PCorr = 0. Coint refers to the Wald test for the presence of cointegration defined by $\beta_1 = \beta_2 = \beta_3 = 0$. Eq shows the cointegration equation (long-run elasticities) between cryptocurrency returns and supply shocks (SS) $R_{ij} = e^t \cdot SS_{ij} + e^t \cdot SS_{ij}$. LAsym refers to the Wald test for the null of long-run symmetry defined by $-\beta_2/\beta_1 = -\beta_3/\beta_1$. SAsym refers to the Wald test for the null of short-run symmetry defined by $\gamma_1 = \gamma_1$. Lags L and Lags S show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for (1)-lags on the rest of relevant cryptocurrencies returns. As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.
Cash, Tether, Bitcoin SV, Litecoin, EOS, Binance coin, Tezos and Cardano) and the risk, demand and supply shocks, respectively, for the pre-COVID-19 sub-period proposed in the present research (from November 20, 2018 to February 28, 2020).

These tables follow the structure of previous Tables 2–4 which displayed the results of the nonlinear ARDL model for the whole sample period.

The Pearson’s correlation coefficients, shown in the second column of Tables 5–7, report that the null hypothesis of no correlation is rejected only by Bitcoin for risk shocks, by four out of eleven cryptocurrencies (Bitcoin, Ethereum, Litecoin and Cardano) for demand shocks and just by Tether for supply shocks in this pre-COVID-19 sub-period. Therefore, a positive and statistically significant correlation at the 10% level is observed between risk shocks and Bitcoin returns, between demand shocks and Bitcoin and Ethereum at 5% and Litecoin and Cardano at 10% statistical significance level and finally, a negative and statistically significant correlation at 10% level is found between supply shocks and Tether.

The results of the Wald’s F test for cointegration, exhibited in the third column of Tables 5–7, show that the null hypothesis of no cointegration is rejected only by Bitcoin cash for risk and supply shocks and by three out of eleven cryptocurrencies (Bitcoin_cash, Tether and Tezos) for demand shocks. So, there would be a long-run connectedness between changes in risk, demand and supply shocks and Bitcoin cash returns and also between demand shocks and Tether and Tezos returns. Moreover, the long-run coefficients of changes in the three components of oil price returns are positive and statistically significant at 10% level for all of them, except in the case of Bitcoin_cash, whose significance level is 5% for demand shocks. Overall, Bitcoin_cash show cointegration for the three components of oil price (risk, demand, and supply) in this pre-COVID-19 sub-period.

The results of the cointegration equation between the eleven cryptocurrencies’ returns and the risk, demand, and supply shock returns, reported in the fourth column of Tables 5–7, evidence that all cryptocurrency returns repond in the same direction to positive and negative changes in the three components of the oil price returns. In addition, all cryptocurrencies show low coefficients in the three oil price components and in all these cases Tether also ranks with the lowest coefficients in this pre-COVID-19 sub-period as it did in the whole sample period. Moreover, the long-run elasticities for the cumulative sum of positive and negative changes in oil price returns are not statistically significant for any cryptocurrency for risk and supply shocks, while these elasticities are positive and statistically significant for Ripple and Tezos for demand shocks.

The results of the Wald test for testing the long-run symmetry, reported in the fifth column of Tables 5–7, show that the null hypothesis of long-run symmetry is not rejected for any of the cryptocurrencies for any of the three components of the oil price return. Thus, according to the Wald test, there is no long-run asymmetry in cryptocurrency returns to changes in the risk, demand, and supply shocks during the pre-COVID-19 sub-period.

The results of the Wald test for examining the short-run symmetry, exhibited in the sixth column of Tables 5–7, show that the null hypothesis of short-run symmetry is rejected only by Tether for supply shocks (Table 7) and this cryptocurrency shows a negative and statistically significant coefficients at the 1% significance level. However, there is no short-run symmetry information for risk and demand shocks in this pre-COVID-19 sub-period. Thus, it is not possible to test for the presence of asymmetric short-run responses, except for the evidence of short-run asymmetry for the case of Tether returns to changes in supply shocks.

The effect of the cumulative sum of positive and negative changes in risk, demand and supply shocks for 1 to 4 lags on the top eleven cryptocurrency returns, reported in the seventh and eight columns of Tables 5–7, show that there is poor perseverance in the effect of positive and negative changes in risk, demand and supply shocks in the pre-COVID-19 sub-period. Specifically, there is a negative and statistically significant effect of the cumulative sum of positive changes in the risk shocks (Table 5) on Litecoin, EOS, and Binance_coin (for 2 lags) and on EOS returns (for 1 lag); in the demand shocks (Table 6) on Ripple, Bitcoin_cash, Tether and Litecoin (for 4 lags) and in the supply shocks (Table 7) on Ripple (for 3 lags), Litecoin (for 4 lags) and EOS (for 1 lag). However, there is only a positive and statistically significant effect of the cumulative sum of positive changes in the demand shocks (Table 6) on Ethereum (for 3 lags). On the other hand, there is a negative and statistically significant effect of the cumulative sum of negative changes in the risk shocks (Table 5) on Ripple returns (for 2 lags); in the demand shocks (Table 6) on Ethereum (for 2, 3 and 4 lags), Ripple (for 2 and 3 lags), Tether (for 2 lags), Bitcoin SV (for 3 lags), Litecoin (for 2 lags), EOS (for 2 lags), Tezos (for 1, 2 and 4 lags) and Cardano (for 2 lags) and finally, in the supply shocks (Table 7) on Bitcoin (for 2 lags), Ethereum (for 2 and 4 lags), Ripple (for 2 lags), Bitcoin SV (for 4 lags) and EOS (for 2 lags). Finally, there is only a positive and statistically significant effect of the cumulative sum of negative changes in the supply shocks (Table 6) on EOS (for 1 lag).

Finally, the explanatory power of the nonlinear ARDL model reported in the ninth column of Tables 5–7 shows that the R² values range from 0.04% (Cardano) to 7.94% (Tether) for risk shocks; from 1.55% (Binance_coin) to 12.64% (Tezos) for demand shocks and from 0.36% (Cardano) to 8.67% (Tether) for supply shocks in the pre-COVID-19 sub-period.

4.2.2. NARDL model estimation: COVID-19 sub-period (March 02, 2020–June 30, 2020)

Tables 8–10 report the regression results of the non-linear ARDL model together with the tests of asymmetry and cointegration between the returns of the top eleven cryptocurrency returns (Bitcoin, Ethereum, Ripple, Bitcoin Cash, Tether, Bitcoin SV, Litecoin, EOS, Binance coin, Tezos and Cardano) and the oil price returns in their different components (risk, demand, and supply shocks) for the COVID-19 pandemic sub-period analysed in the present research (from March 2 until June 30, 2020).

These tables maintain a similar structure to the tables studied in the periods previously analysed.

The Pearson’s correlation coefficient (column 2 of Tables 8–10), indicates that the null hypothesis of no correlation is rejected by all eleven cryptocurrencies for risk and demand shocks, while this null hypothesis is not rejected by any cryptocurrency for supply shocks. Specifically, a negative correlation is observed between changes in risk shocks (Table 8) and all cryptocurrency returns, except for Tether that shows a positive correlation coefficient around 30%. However, a positive correlation is found between changes in demand shocks (Table 9) and all cryptocurrency returns, except for Tether that shows a negative correlation coefficient around –27%. Thus, all cryptocurrencies except Tether present a statistical significance at the 1% level, showing Pearson correlation coefficients between –52.24% and –64.87% for risk shocks and between 45.67% for Bitcoin and Ethereum and 50.14% for Binance coin.

The Wald F test (column 3 of Tables 8–10) establishes that the null hypothesis of no cointegration is rejected by all cryptocurrencies, except for Bitcoin SV for risk shocks, by all eleven cryptocurrencies for demand shocks and by all cryptocurrencies except for Bitcoin_cash and Bitcoin SV for supply shocks. Therefore, it assumes the maintenance of a long-run connectedness between changes in risk, demand, and supply shocks and virtually all cryptocurrencies’ returns in the COVID-19 sub-period. Moreover, the long-run coefficients of changes in the three components of oil price returns are positive and statistically significant at 1% level in most cryptocurrencies. In addition, Tether is the cryptocurrency whose F-statistic presents the highest values for risk and demand shocks and also a high value for supply shocks. These results show evidence in line with previous literature, which advocates the idea that there is a higher degree of interdependence between financial variables in periods of economic turbulence such as the COVID-19 pandemic (Jareño et al., 2020).

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Table 8
Regression results of non-linear ARDL models and asymmetry and cointegration tests between dominant cryptocurrency returns and changes in oil prices: Risk Shocks (RS) in the COVID-19 subperiod (March 2-June 30, 2020).

| Cryptocurrencies | PCorr  | Coint  | Eq     | LAsym  | SAsym  | Lags ⁺ | Lags ⁻ | Adj. R²   |
|------------------|--------|--------|--------|--------|--------|--------|--------|----------|
| Bitcoin          | -0.5224*** | 2.7126** | e: -1.5368E-03 | 0.0005 | - | (3): -0.0014* | (4): -0.0041*** | 0.4367 |
| Ethereum         | -0.5692*** | 3.7526** | e: -0.0008 | 0.1479 | - | (3): -0.0020** | (4): -0.0053*** | 0.5006 |
| Ripple           | -0.5512*** | 5.3651*** | e: -1.2793E-03 | 0.0028 | - | (3): -0.0018** | (2): -0.0027* | 0.5532 |
| Bitcoin_cash     | -0.5372*** | 2.3862* | e: -0.0027 | 0.2158 | - | - | (4): -0.0058*** | 0.4889 |
| Tether           | 0.2968*** | 6.6592** | e: 2.8469E-05 | 2.1007 | - | (2): -3.38E-05* | (3): 9.74E-05** | 0.4926 |
| Bitcoin_yx       | -0.5583*** | 1.6347 | e: -0.0054 | 0.0319 | - | - | (4): -0.0068*** | 0.4802 |
| Litecoin         | -0.5761*** | 4.9212*** | e: -0.0020 | 0.2147 | - | - | (4): -0.0046*** | 0.5283 |
| EOS              | -0.5538*** | 4.6836*** | e: -0.0018 | 0.4417 | - | (3): -0.0019** | (2): -0.0034* | 0.5392 |
| Binance_coin     | -0.5890*** | 3.2586** | e: -0.0024 | 0.0344 | - | (3): -0.0015* | (4): -0.0061*** | 0.5355 |
| Tezos            | -0.6487*** | 3.8622** | e: -0.0011 | 0.0607 | - | (3): -0.0022** | (4): -0.0049*** | 0.5624 |
| Cardano          | -0.5993*** | 2.2723* | e: 0.0012 | 0.6792 | - | - | - | 0.4052 |

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency returns and oil price shocks. **PCorr** refers to the Pearson’s correlation coefficients defined by the null of PCorr = 0. **Coint** refers to the Wald test for the presence of cointegration defined by β₁ = β₂ = β₃ = 0. **Eq** shows the cointegration equation (long-run elasticities) between cryptocurrency returns and risk shocks (RS) Rₛₑᵣ = eᵢᵣ. **SAsym** refers to the Wald test for the null of short-run symmetry defined by γᵢᵣ = γᵢᵣ. **Lags ⁺** and **Lags ⁻** show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for (1)-lags on the rest of relevant cryptocoins returns.

As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.

Table 9
Regression results of non-linear ARDL models and asymmetry and cointegration tests between dominant cryptocurrency returns and changes in oil prices: Demand Shocks (DS) in the COVID-19 subperiod (March 2-June 30, 2020).

| Cryptocurrencies | PCorr  | Coint  | Eq     | LAsym  | SAsym  | Lags ⁺ | Lags ⁻ | Adj. R²   |
|------------------|--------|--------|--------|--------|--------|--------|--------|----------|
| Bitcoin          | 0.4567*** | 6.8713*** | e: 0.0145*** | 0.1893* | 4.1691*** | (3): -0.0079** | (2): -0.0054* | 0.4796 |
| Ethereum         | 0.4567*** | 8.3652*** | e: 0.0138*** | 1.0132 | 4.6541*** | (3): -0.0072* | (2): -0.0117*** | 0.5987 |
| Ripple           | 0.4793*** | 6.9091*** | e: 0.0051** | 0.0399 | 4.3800*** | (2): 0.0053** | (4): -0.0093** | 0.4980 |
| Bitcoin_cash     | 0.4792*** | 6.2296*** | e: 0.0049* | 0.4682 | 5.4099** | - | (2): -0.0062* | 0.5600 |
| Tether           | -0.2739** | 15.5714*** | e: 2.1992E-04* | 0.7328 | - | - | (4): -0.0093* | 0.6105 |
| Bitcoin_yx       | 0.4696*** | 9.3215*** | e: 0.0074*** | 0.2986 | 4.9325*** | (3): -0.0096** | (2): -0.0099** | 0.5161 |
| Litecoin         | 0.4814*** | 7.7679*** | e: 0.0093** | 0.3105 | 5.3715*** | - | (2): -0.0069** | 0.6062 |
| EOS              | 0.4648*** | 8.5086*** | e: 0.0220** | 0.5755 | 5.0176*** | (3): -0.0081** | (4): -0.0071** | 0.5284 |
| Binance_coin     | 0.5014*** | 10.0661*** | e: 0.0202** | 0.6740 | 6.0560*** | (3): -0.0084** | (3): 0.0147*** | 0.5896 |
| Tezos            | 0.4955*** | 8.3841*** | e: 0.0342** | 1.2138 | 5.2752** | (3): -0.0086** | (2): 0.0127** | 0.6124 |
| Cardano          | 0.4898*** | 3.0142** | e: 0.0056 | 0.7610 | 5.5174*** | - | - | 0.4031 |

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency returns and oil price shocks. **PCorr** refers to the Pearson’s correlation coefficients defined by the null of PCorr = 0. **Coint** refers to the Wald test for the presence of cointegration defined by β₁ = β₂ = β₃ = 0. **Eq** shows the cointegration equation (long-run elasticities) between cryptocurrency returns and demand shocks (DS) Rₛₑᵣ = eᵢᵣ. **LAsym** refers to the Wald test for the null of long-run symmetry defined by ‐β₂/β₁ = ‐β₃/β₁. **SAsym** refers to the Wald test for the null of short-run symmetry defined by γᵢᵣ = γᵢᵣ. **Lags ⁺** and **Lags ⁻** show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for (1)-lags on the rest of relevant cryptocoins returns.

As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.
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Table 10
Regression results of non-linear ARDL models asymmetry and cointegration tests between dominant cryptocurrency returns and changes in oil prices: Supply Shocks (SS) in the COVID-19 subperiod (March 2–June 30, 2020).

| Cryptocurrencies | PCorr   | Coint   | Eq     | LAsym  | SAsym  | Lags  | Lags  | Adj. R² |
|------------------|---------|---------|--------|--------|--------|-------|-------|--------|
| Bitcoin          | 0.0031  | 3.4439**| e⁺: 0.0011| 1.9018 | -      | (2): -0.0022| 0.1594|
| Ethereum         | -0.0285 | 4.6504***| e⁺: 0.0014| 1.9450 | -      | -     | 0.1534|
| Ripple           | -0.0379 | 5.2318***| e⁺: 0.0021***| 0.3325 | -      | (3): 0.0022*| 0.2014|
| Bitcoin_cash     | 0.0264  | 1.9806  | e⁺: 0.0012| 0.5509 | -      | -     | 0.1144|
| Tether           | 0.0510  | 3.9308***| e⁺: -5.968E-06| 0.0043 | -      | (1): -6.49E-05| 0.2638|
| Bitcoin_sv       | 0.0472  | 1.4822  | e⁺: 0.0023| 0.2850 | -      | -     | 0.0546|
| Litecoin         | -0.0100 | 4.9217***| e⁺: 0.0008| 1.2244 | -      | -     | 0.2024|
| EOS              | -0.0016 | 3.3915**| e⁺: 0.0012| 0.9820 | -      | -     | 0.1167|
| Binance_coin     | -0.0228 | 3.5228**| e⁺: 0.0015| 0.9111 | -      | -     | 0.1207|
| Tezos            | -0.0104 | 4.0739***| e⁺: 0.0019| 0.7524 | -      | -     | 0.1370|
| Cardano          | -0.0401 | 4.2593***| e⁺: 0.0016| 3.3569*| -      | -     | 0.1423|

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency returns and oil price shocks. PCorr refers to the Pearson’s correlation coefficients defined by the null of PCorr = 0. Coint refers to the Wald test for the presence of cointegration defined by β₁ = β₂ = β₃ = 0. Eq shows the cointegration equation (long-run elasticities) between cryptocurrency returns and supply shocks (SS); SSS = e⁺ · SSS × e⁻ · SS × e⁻ · LAsym refers to the Wald test for the null of long-run symmetry defined by -β₂β/β₁ = -β₂β/β₁. SAsym refers to the Wald test for the null of short-run symmetry defined by γ⁺ = γ⁻. Lags + and Lags − show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for (l)-lags on the rest of relevant cryptocurrencies returns.

As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.

Table 10 (continued)

2020; Umar et al., 2020, among others).

The cointegration equation (column 4 of Tables 8–10) points out that all cryptocurrency returns respond in the same way to positive and negative changes in oil price, demand, and supply shocks. Moreover, the coefficients are low, and Tether ranks with the lowest coefficients in the COVID-19 sub-period as it did in the full period and the pre-COVID-19 sub-period. In addition, the long-run elasticities for the cumulative sum of positive and negative changes in oil price returns are not statistically significant for any cryptocurrency for risk shocks, while these elasticities are positive and statistically significant for all cryptocurrencies except for Tether that shows negative and statistically significant coefficients for demand shocks, causing movements in the opposite direction to these shocks and finally, for supply shocks, the long-run elasticities are positive and statistically significant for Ripple and Cardano.

The Wald test for detecting long-run symmetry (column 5 of Tables 8–10) reports that the null hypothesis of long-run symmetry is not rejected for any of the eleven cryptocurrencies for the risk shocks, but it is rejected by Bitcoin for the demand shocks as well as by Cardano for the supply shocks. Thus, according to the Wald test, there is a possible asymmetry in the long-run impact of changes in the demand shocks for Bitcoin and in the supply shocks for Cardano during the COVID-19 sub-period.

The Wald test for examining short-run symmetry (column 6 of Tables 8–10) shows that the null hypothesis of short-run symmetry is rejected by all cryptocurrencies for demand shocks (Table 9) which exhibit high positive and statistically significant coefficients at the 1% level. On the other hand, there is no information on short-run symmetry for risk and supply shocks in the COVID-19 sub-period. Thus, there is evidence of asymmetries in the short-run for all cryptocurrencies’ returns to changes in demand shocks.

The effect of the cumulative sum of positive and negative changes in oil price, demand and supply shocks for 1 to 4 lags on the eleven cryptocurrency returns (columns 7 and 8 of Tables 8–10) shows that there is a high persistence in the effect of positive and negative changes in risk and demand shocks, for 1 to 4 lags, for most cryptocurrency returns. Thus, there is a slightly lower impact of increases than decreases of oil price returns on most cryptocurrencies’ returns. Moreover, there is a negative and statistically significant effect of the cumulative sum of positive changes in the risk shocks (Table 8) on Bitcoin, Ethereum, Ripple, EOS, Binance_coin and Tezos returns (for 3 lags) and on Tether returns (for 2 lags); in the demand shocks (Table 9) on Bitcoin, Ethereum, Bitcoin_sv, Litecoin, EOS, Binance_coin and Tezos returns (for 3 lags) and in the supply shocks (Table 10) on Tether (for 1 lag). Additionally, there is a positive and statistically significant effect of the cumulative sum of positive changes in the demand shocks (Table 9) on Ripple returns (for 2 lags) and in the supply shocks (Table 10) on Tether returns (for 2 lags). On the other hand, there is a negative and statistically significant effect of the cumulative sum of negative changes in the risk shocks (Table 8) on Bitcoin, Ripple, Binance_coin, Bitcoin_sv, EOS, Binance_coin and Tezos returns (for 3 lags) and in the supply shocks (Table 9) on Bitcoin and Ripple returns (for 2 lags) and on Ripple and EOS returns (for 2 lags); in the demand shocks (Table 9) on Ethereum (for 4 lags) and on Tether (for 3 lags) and in the supply shocks (Table 10) on Bitcoin (for 2 lags). Finally, there is a positive and statistically significant effect of the cumulative sum of negative changes in the risk shocks (Table 8) on Tether (for 3 and 4 lags); in the demand shocks (Table 9) on Bitcoin, Ethereum, Bitcoin_sv, EOS and Binance_coin (for 2 and 3 lags), on Ripple (for 3 lags), on Bitcoin_cash, Litecoin and Tezos (for 2, 3 and 4 lags).

Finally, the explanatory power of the nonlinear ARDL model (column 9 of Tables 8–10) shows that the R² values range from 40.52% (Cardano) to 56.24% (Tezos) for risk shocks; from 40.31% (Cardano) to 61.24% (Tezos) for demand shocks and from 5.46% (Bitcoin_sv) to 26.38% (Tether) for supply shocks in the COVID-19 sub-period. We observe that, in this sub-period of health, economic and financial crisis, the explanatory power of the model is much higher than in the other periods analysed.
5. Concluding remarks

The present research seeks to analyse the impact generated by the COVID-19 pandemic on the long- and short-run interdependencies between changes in the price of oil (broken down into its three components: demand, supply and risk shocks) and the cryptocurrency market through the NARDL approach. Specifically, the cryptocurrency market is represented in this paper by the eleven digital currencies with the highest volume of market capitalization during most of the sample period analysed: Bitcoin, Ethereum, Ripple, Bitcoin_cash, Tether, Bitcoin_sv, Litecoin, EOS, Binance_coin, Tezos and Cardano. The sample period runs from November 20, 2018 to June 30, 2020. For greater robustness of the results, the analysis has been divided into two different sub-sample periods: the pre-COVID-19 sub-period (from November 20, 2018 to February 28, 2020) and the COVID-19 sub-period (from March 2 to June 30, 2020), thus focusing on the first wave of the SARS-CoV-2 pandemic.

Our results show that there is a higher degree of interconnection between oil price shocks and cryptocurrency returns in periods of crisis since the NARDL model explains more than 56%, 61% and 26% of the leading cryptocurrency returns with risk, demand and supply shocks, respectively, for the COVID-19 sub-period. This result is between 5 and 7 times higher than that in the whole period and the pre-COVID-19 sub-period, respectively. Therefore, in line with what has been previously established in much of the financial literature, the results are more robust in extreme market conditions.

The main conclusions of this paper are the following ones. First, there is a high, positive and statistically significant correlation between demand shocks to oil prices and all the leading cryptocurrencies, except Tether, over the whole sample period and to a greater degree during the COVID-19 sub-period. Moreover, there exists a negative and statistically significant correlation between risk shocks to oil prices and all considered cryptocurrencies, except Tether, over the entire period and especially during the coronavirus episode. However, there is no evidence of correlation between supply-side shocks and cryptocurrencies for any period. Second, a positive long-term relationship, or cointegration, is found between most cryptocurrency returns and changes in the oil price (in each of its components) in the sub-period of crisis triggered by COVID-19. However, for the full period and the pre-COVID-19 sub-period, cointegration is only observed for a few cryptocurrencies. Third, the cointegration equation reveals that cryptocurrency returns tend to respond in the same way to positive and negative changes in crude oil price returns, with very few exceptions. Moreover, the long run-elasticities for the cumulative sum of positive and negative changes in demand shocks are statistically significant for all cryptocurrencies in the COVID-19 sub-period and for most cryptocurrencies in the full period. Additionally, Tether responds the least to positive and negative changes in the three components of oil price returns in all periods. Fourth, there is no evidence of asymmetries in the long-term impact of different oil price shocks on the analysed cryptocurrency returns for the three periods considered. However, in the COVID-19 sub-period, the results identify a possible long-term asymmetric relationship between demand-side shocks and Bitcoin, and between supply-side shock and Cardano. Despite this, there is a notable indication of short-run asymmetries between demand shocks and all the cryptocurrency returns in all periods.

Finally, we also find a statistically significant effect of the cumulative sum of oil price changes, for 1 to 4 lags, on cryptocurrency returns, which is especially relevant for demand-side shocks in all periods, and especially in the COVID-19 sub-period. According to these results, clear differences are observed in the impact of changes in the price of crude oil on the returns of the analysed cryptocurrencies, as the range of values of the explanatory power changes depending on the subperiod analysed, but always being extremely higher in the COVID-19 sub-period. Therefore, these results would evidence a different effect of changes in the price of oil on the returns of the virtual currencies included in the study, depending on the market situation. These findings would be in line with some previous studies and would require a deeper analysis on the causes behind them. To be more specific, within this range of R^2 values, the demand component is consistently the one that shows the greatest explanatory power in all periods, and in all cases Tezos is the cryptocurrency that shows the maximum R^2, and, as we have already mentioned, especially in the COVID-19 sub-period. Therefore, it can be concluded that the results offered by the NARDL methodology selected for this research are totally suitable given that it reaffirms what was previously pointed out by previous literature regarding the probability that the pattern of interdependence between financial variables is modified according to the economic circumstances of the market, such as the exceptional situation caused by the COVID-19 pandemic.

Additionally, Tether deserves special attention for several reasons: First, Tether is the cryptocurrency least connected to the three components of oil price returns and thus, it could be used for diversification strategies or even act as a safe-haven. Second, Tether behaves the opposite to the other cryptocurrencies in the correlation analysis, probably because it is a more stable currency with a unit value of one US dollar. Concretely, all cryptocurrencies are positively (negatively) correlated to demand shocks (risk shocks) in the whole sample period and the COVID-19 sub-period, except Tether, which shows a negative (positive) correlation coefficient. Third, Tether shows high R^2 values in all periods for all three oil price components, but especially in the COVID-19 sub-period. The results of the present study are of great importance to both investors and policy makers. On the one hand, as previously noted, the lower level of correlation between Tether and crude oil shocks in comparison to other cryptocurrencies, which is robust to the pandemic crisis period, offers investors and portfolio managers a meaningful channel for risk diversification. On the other hand, in a context of growing popularity of cryptocurrencies in many countries, governments and policy makers should be aware of the significant impact that crude oil shocks (especially demand-side shocks and risk shocks) may have on the stability of the cryptocurrency market. Moreover, it is necessary to consider that the sources of changes in crude oil prices may suffer long-lasting disturbances. Thus, while the months following the outbreak of the coronavirus crisis witnessed the biggest slump in demand for oil ever recorded, recent forecasts from the Energy Information Administration (EIA) reveal that global oil demand will still be below pre-pandemic levels by the end of 2021, thus showing that demand-side shocks may be long-term in nature.

Finally, some lines of future research could imply conducting an in-depth analysis of the roles that cryptocurrencies can play as either a diversifier, a hedge, or a safe haven against other traditional assets, principally during periods of economic turmoil, with the aim of contributing to the existing financial literature. On the other hand, given the unprecedented rise in cryptocurrency prices, in particular Bitcoin, beyond the first wave of the COVID-19 pandemic analysed in this research, it would also be interesting to extend the study on the connection between the cryptocurrency market and other financial markets, due to the important role in financial contagion that the herd effect of investors could play. As it is well known, herding would confirm that investment decisions in some cryptocurrencies is not only motivated by the attributes of individual currencies but by the attractiveness of the market as a whole. Thus, in certain scenarios, herding could very well explain the observed price patterns in the cryptocurrency market.

Data availability statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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Corbet, S., Hou, Y.G., Hu, Y., Larkin, C., Osley, L., 2020b. Any port in a storm: cryptocurrency safe-havens during the COVID-19 pandemic. Econ. Lett. 194 (108878) https://doi.org/10.1016/j.econlet.2020.108878.

Corbet, S., Larkin, C., Lacey, B., 2020c. The contagion effects of the COVID-19 pandemic: evidence from gold and cryptocurrencies. Finance Res. Lett. 35 (101554) https://doi.org/10.1016/j.frl.2020.101554.

Corbet, S., Lucey, B., Urquhart, J., Varayoya, L., 2019. Cryptocurrencies as a financial asset: a systematic analysis. Int. Rev. Financ. Anal. 62, 182-199.

Dan, D., Roux, C.L.L., Jana, R.K., Dutta, A., 2020. Does Bitcoin hedge crude oil implied volatility and structural shocks? A comparison with gold, commodity and the US Dollar. Finance Res. Lett. 36 (101335) https://doi.org/10.1016/j.frl.2020.101335.

Demir, E., Simonyan, S., García-Cómez, D., Lau, K.C.M., 2021. The asymmetric effect of bitcoin on alcoho: evidence from the nonlinear autoregressive distributed lag (NARDL) model. Finance Res. Lett. 101754 https://doi.org/10.1016/j.frl.2020.101754.

Diebold, F., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119, 158–171. https://doi.org/10.1111/j.1468-0297.2008.02151.x.

Ferrero, R., Shahzad, S.J.H., Lopez, R., Jareno, F., 2018. Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. Energy Econ. 76, 1-20. https://doi.org/10.1016/j.eneco.2018.09.022.

Ghazani, M.M., Khorasani, R., 2020. Multifractal detrended cross-correlation analysis on benchmark cryptocurrencies and crude oil prices. Physica A 560, 125172. https://doi.org/10.1016/j.physa.2020.125172.

Gonzalez, M., Jareno, F., Skinner, F., Bagnoli, En C., Billio, M., Varotto, S., 2020a. Portfolio effects of cryptocurrencies during the COVID-19 crisis. In: A New World Post COVID-19: Lessons For Business, the Finance Industry and Policy Makers. Edizioni Ca Foscari - Digital Publishing, Venezia, pp. 149–161. https://doi.org/10.3390/books9896944234.

Gonzalez, M., Jareno, F., Skinner, F., 2020b. Nonlinear autoregressive distributed lag approach: an application on the connectedness between bitcoin returns and the other ten most relevant cryptocurrency returns. Mathematics 8 (10) https://doi.org/10.3390/math8101010.

Gonzalez-Moreno, J., Jareno, F., Skinner, F.S., 2021. Asymmetric interdependencies between large capital cryptocurrency and gold returns during the COVID-19 pandemic crisis. Int. Rev. Financ. Anal. 76, 101773. https://doi.org/10.1016/j.irfa.2021.101773.

Goodell, J.W., Goutte, S., 2021. Diversifying equity with cryptocurrencies during COVID-19. Int. Rev. Financ. Anal. 76 (101781) https://doi.org/10.1016/j.irfa.2021.101781.

Guesmi, K., Saadi, S., Abid, I., Pitti, Z., 2019. Portfolio diversification with virtual currency: evidence from bitcoin. Int. Rev. Financ. Anal. 63, 431-437.

Guo, X., Lu, F., Wei, Y., 2021. Capture the contagio network of bitcoin – evidence from pre and mid COVID-19 crisis. Res. Int. Bus. Finance 58 (101484) https://doi.org/10.1016/j.resourpol.2020.101898.

Kalyuzhnova, Y., Lee, J., Bagnoli, E., Billio, M., Varotto, S., 2020. Will COVID-19 outbreak in the world and cryptocurrency market. Int. Rev. Financ. Anal. 74, 100836. https://doi.org/10.1016/j.irfa.2020.100836.

Karamti, C., Bellhassine, O., 2021. COVID-19 pandemic waves and global financial markets: evidence from wavelet coherence analysis. Finance Res. Lett. 76 https://doi.org/10.1016/j.frl.2020.101781.

Karamti, C., Bellhassine, O., 2021. COVID-19 pandemic waves and global financial markets: evidence from wavelet coherence analysis. Finance Res. Lett. 76 https://doi.org/10.1016/j.frl.2020.101781.

Karamti, C., Bellhassine, O., 2021. COVID-19 pandemic waves and global financial markets: evidence from wavelet coherence analysis. Finance Res. Lett. 76 https://doi.org/10.1016/j.frl.2020.101781.

Karamti, C., Bellhassine, O., 2021. COVID-19 pandemic waves and global financial markets: evidence from wavelet coherence analysis. Finance Res. Lett. 76 https://doi.org/10.1016/j.frl.2020.101781.
Sharif, A., Aloui, C., Yarovaya, L., 2020. COVID-19 pandemic, oil prices, stock market, 
Shin, Y., Yu, B., Greenwood-Nimmo, M.J., 2014. Modelling asymmetric cointegration 
and dynamic multipliers in a nonlinear framework. In: Horrace, W.C., Sickles, R.C. (Eds.), Festschrift in honor of Peter Schmidt. Springer, Science & Business Media, New York, NY.
Smales, L.A., 2019. Bitcoin as a safe haven: is it even worth considering? Finance Res. Lett. 30, 385–393.
Symitsi, E., Chalvatizis, K.J., 2019. The economic value of Bitcoin: a portfolio analysis of currencies gold and stocks. Res. Int. Bus. Finance 48, 97–110. https://doi.org/10.1016/j.ribaf.2018.12.001.
Tu, Z., Xue, C., 2019. Effect of bifurcation on the interaction between bitcoin and 
Litecoin. Finance Res. Lett. 31, 382–385. https://doi.org/10.1016/j.frl.2018.12.010.
Umar, Z., Jareño, F., Escrivano, A., 2020. Static and dynamic connectedness between oil 
price shocks and Spanish equities: a sector analysis. Eur. J. Finance. https://doi.org/10.1080/1351847X.2020.1854809.
Umar, Z., Jareño, F., Escrivano, A., 2021a. Agricultural commodity markets and oil 
prices: an analysis of the dynamic return and volatility connectedness. Resour. Pol. 73, 102147. https://doi.org/10.1016/j.resourpol.2021.102147.
Umar, Z., Jareño, F., Escrivano, A., 2021b. Oil price shocks and the return and volatility 
spillover between industrial and precious metals. Energy Econ. 99, 105291. https://
doi.org/10.1016/j.eneco.2021.105291.
Umar, Z., Jareño, F., González, M., 2021c. The impact of COVID-19 related media 
coverage on the return and volatility connectedness of cryptocurrencies and fiat 
currencies. Technol. Forecast. Soc. Change 172, 121025. https://doi.org/10.1016/j.
techfore.2021.121025.
Waltner, T., Klein, T., Bouri, E., 2019. Exogenous drivers of Bitcoin and Cryptocurrency 
volatility—a mixed data sampling approach to forecasting. J. Int. Financ. Mark. Inst. Money 63, 101–133. https://doi.org/10.1016/j.intfin.2019.101133.
Yarovaya, L., Breznayczynski, J., Goodell, J., Lucey, B., Lau, C., 2020a. Rethinking 
financial contagion: information transmission mechanism during the COVID-19 
pandemic. SSRN 1–46. https://doi.org/10.2139/ssrn.3602973.
Yarovaya, L., Matkovsky, R., Jalan, A., 2020b. The effects of a ‘black swan’ event 
(COVID-19) on herding behavior in cryptocurrency markets: evidence from 
cryptocurrency USD, EUR, JPY and KRW markets. SSRN, pp. 1–57. https://
doi.org/10.2139/ssrn.3586511.
Yin, L., Nie, J., Han, L., 2021. Understanding cryptocurrency volatility: the role of oil 
market shocks. Int. Rev. Econ. Finance 72, 233–253. https://doi.org/10.1016/j.
trevfin.2020.11.013.
Yousaf, I., Ali, S., 2020. The COVID-19 outbreak and high frequency information 
transmission between major cryptocurrencies: evidence from the VAR-DCC-GARCH 
approach. Borsa istanbul Review. https://doi.org/10.1016/j.bir.2020.10.003.