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Research article

Asymmetric interdependencies between cryptocurrency and commodity markets: the COVID-19 pandemic impact

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Abstract: Using NARDL methodology, this research investigates some asymmetric and non-linear interconnections between leading cryptocurrency and commodity returns. Thus, this study explores potential interconnections between these cryptocurrencies and commodity markets in the period between March 07, 2018, and March 26, 2021. This paper splits the entire sample period into two independent sub-periods in order to enhance robustness: pre-COVID and COVID, to examine the impact of the pandemic on these markets. Our results confirm that the most relevant interconnection (in terms of cointegration, short- and long- asymmetry, and the persistence of the lags) between cryptos and commodities is focused on COVID-19, the pandemic sub-period, in line with previous literature. Finally, the study reveals that some cryptocurrencies such as Tether could serve as a diversifying asset or even a safe haven, in certain scenarios, in investment strategies.

Keywords: cryptocurrencies; NARDL; commodity markets; COVID-19

JEL Codes: C22, C51, F21, H12

1. Introduction

During the first months of 2019, the SARS-CoV-2 coronavirus caused a pandemic that has meant an impact of great dimension in all aspects, at the economic, financial, social, political and even cultural level. In a globalized environment, the problems of one country can spread to the rest in a matter of weeks.

Thus, the pandemic has also led to a very considerable economic decline in most of the world's countries in 2020 (in Spain, GDP fell by 11%) and has negatively affected the markets for all products. The impact on financial markets has been remarkable and the volatility of the last year of financial assets has been the common note of a great part of them, specifically, cryptocurrencies have reached this last year their maximum variations and also minimum in terms of returns, which reflects the most acute effect of the pandemic in this market.

According to the above, the worldwide outbreak has supposed an important downturn in the commodity market. Even now, the mitigation measures have also affected the commodity market. For example, restrictions in travelling or complete lockdowns in many countries suppose important consequences in demand of commodities. The oil market reduced his demand (and price) in March 2020. Likewise, metal prices also have a declining trend. Finally, the agriculture sector is less affected by the pandemic due to it is a sector in relation with economic activities and the food security is a primary objective.

The relevance of the cryptocurrency market for several years and the progression that exists since the beginning of the pandemic (before the COVID-19 pandemic there were about 5000 cryptocurrencies in circulation and by the end of March 2021 there are about 8400 cryptocurrencies circulating in the market) leads us to analyse in this paper part of its market. Specifically, this paper analyses the four main cryptocurrencies, Bitcoin, Ethereum, Cardano and Tether, in terms of their market capitalization value over much of the period analysed. These four cryptocurrencies dominate 75% of the market (Bitcoin has a dominance of 59.42% of the market, Ethereum 11.09%, Cardano 2.16% and Tether 2.30%), which is noteworthy, since these are only four cryptocurrencies during the period examined in this study out of over 8400 cryptocurrencies in circulation.

In addition, this study is carried out in order to complement part of the economic literature that we will detail, since, as we will see, there is hardly any literature on the effect of COVID-19 on the interdependence between the cryptocurrency market and the mixture of commodity markets selected in this paper. Also, to contribute to the previous literature, a selection of different leading commodities has been made that have hardly been studied together before, such as gold, platinum, natural gas, corn and cotton.

This study aims to achieve up to three main objectives. Firstly, and as the most basic content of the work, to learn about the evolution of the interdependence between the cryptocurrency market and the commodities market, as well as to evaluate the effects of the pandemic on this interdependence. Secondly, and closely related to the above, to find out whether cryptocurrencies are investment diversification instruments or whether their main function is that of a safe haven investment that does not suffer the effects of an economic crisis, as has been pointed out in part of the financial literature. Finally, it is also relevant the inclusion of several commodities of different nature that allow us a comparative study of them and the evolution of their interdependence with the cryptocurrency market.

The paper will differentiate up to three time periods of analysis. The first period covers the entire sample period and runs from March 1, 2018 to March 26, 2021. It was decided to divide the sample period into two sub-periods, which would be used to test the robustness of the results: the first pre-COVID sub-period runs from March 1, 2018 to March 11, 2020, the date of pandemic declaration by the World Health Organization (WHO). The second sub-period comprises from March 12, 2020 to March 26, 2021, the most recent date of data collection.

Thus, the contribution of this paper is three-fold. First, this paper uses the NARDL methodology that allows us to separate the impact that positive and negative changes of commodity returns would have on cryptocurrency returns. In addition, the NARDL approach allows exploring both possible short- and long-term asymmetries in the studied interdependencies between the selected cryptocurrency and commodity returns. Thirdly, the study analyses a relatively recent period and, furthermore, in order to compare how robust the findings were, the entire period was divided into three quarters a sub-period prior to the declaration of the global pandemic (pre-COVID) and another one that explores the pandemic period (COVID), which allows drawing relevant conclusions about a period of turbulence such as the one starred by the SARS-CoV-2 coronavirus.

Thus, to the best knowledge, our paper contributes to previous literature, such as Kwapień et al. (2021), in several aspects. Firstly, the methodology used is richer than that applied in other works, in the sense that it explores different aspects of the potential interdependencies between the returns of the four main cryptocurrencies and the selected commodity markets. The NARDL methodology used in this study allows us to analyse not only the level of cross-correlation between the selected assets, but also the existence of asymmetries in the short- and long-term interdependencies, as well as the cumulative impact of positive and negative changes in the returns of the commodities studied, and the persistence of these effects. Secondly, our research explores the full sample period in order to, subsequently, perform a robustness check, proposing the decomposition into two tranches in which, according to previous literature, the results obtained are expected to be different (before and during the COVID-19 pandemic). Finally, our research differs from previous studies in the sense that the selected commodities correspond to markets of different nature, corresponding to different sectors (energy, agriculture, precious metals), so that potential diverse interdependencies with cryptocurrencies could have important implications in terms of economics and portfolio management.

This research confirms that interdependencies between commodity and cryptocurrency markets are mainly focused on the COVID-19 pandemic period, in terms of cointegration, short- and long-term asymmetry, lag persistence, etc., in line with previous literature, such as González et al. (2021), Jareño et al. (2021) and Kwapień et al. (2021) among others. Therefore, the results of this analysis might have relevant implications for the different crypto and commodity markets, but also for portfolio management.

This work is divided into five sections with the following structure. Section 1 introduces the subject of study in this work with the objectives of the study. A review of current economic and financial research is presented in the second section of the paper, including the main studies carried out on the cryptocurrency market, the commodities market, as well as the works that have studied the interconnection between both markets. Section 3 presents the data used in the sample period, which analyses the main variables of the study by means of the main descriptive statistics and, finally, presents the methodology and equations of the regression model used in the study. Section 4 analyses the results obtained in the estimation with respect to the methodology described above. Specifically, this is a nonlinear autoregressive distributed lag (NARDL) methodology. This section is subdivided into three subsections that will analyse separately the complete sample period, the sub-periods before and during the COVID pandemic, respectively. The last section will include the main conclusions of the analysis carried out throughout the work, as well as some implications of the results and future lines of study.

2. Literature review

The arrival of cryptocurrencies has represented an alternative to the conventional financial system that has detractors and sympathizers in the theoretical and social sphere. The fact that it is a decentralized asset and absent of government regulation means an increase in criticism and distrust in the face of a possible crisis in this market. At the same time, it has attracted the attention of investors, especially after the COVID-19 pandemic, because of the attractiveness of investing in this market due to its high profitability, especially since the beginning of 2021, reaching the historical maximum capitalisation of this market, 22.6 billion dollars, in mid-April 2021, due to the confidence placed by investors in cryptocurrencies as a safe-haven in times of pandemic.

In contrast, as a result of COVID-19, all product markets have been negatively affected, and the commodities market, specifically. Thus, the purpose of this paper is to explore how this pandemic can affect the interdependences between the cryptocurrency market and the commodities market by applying the Nonlinear Autoregressive Distributed Lag (NARDL) approach.

A first branch of recent literature is focused on analysing connectedness between cryptocurrencies, such as Gonzalez et al. (2020a) that, based on the NARDL model, analyses Bitcoin in comparison to the top ten cryptocurrencies by market cap, highlighting the interdependencies between cryptocurrencies and the long-term relationships between them. In the same line, Ciaian et al. (2018) compares Bitcoin with 16 alternative cryptocurrencies, highlighting that they are highly independent cryptocurrencies and have a greater short-term than long-term relationship. As we can see, the conclusions are contradictory, so it is possible that there will be a paradigm shift in relationships over the years. Like the previous study, it makes use of the NARDL methodology for comparison. A study by Demir et al. (2021) finds an asymmetric effect of Bitcoin on three altcoins over the short run when using the NARDL model. The study of asymmetry in terms of whether changes in specific explored variables are positive and negative is also discussed in many other papers analysing the cryptocurrency market such as Ante (2020).

The second branch of the literature analyses the relationships that exist between commodities (Umar et al., 2021a, 2021b). A relevant study is the one conducted by Balli et al. (2019) on the connection existing in 22 commodities at a time of uncertainty as was the global financial crisis and the collapse of the price of crude oil between 2014 and 2016. They consider that in the long-run commodity markets are interconnected in their effects and that precious metals are one of the safest commodities during the referred crisis periods. In addition, Ahdmadi et al. (2016) also studies the volatility of the commodity market (specifically agricultural products and metals) but related to oil price shocks. They use an SVAR model and distinguishes two time periods: prior to the financial crisis and afterwards. In principle, the effects of oil prices on commodities are of short duration and the effects were much more pronounced during the financial crisis. Nazlioglu (2011) further emphasizes the idea that the price of crude oil directly affects three agricultural commodities (soybeans, wheat and corn), thanks to a linear Granger causality model, although this author recognises that there are local commodities not affected by the crude oil market. Ferrer et al. (2018), following a VAR model and denying the involvement of crude oil prices in price differences in renewable energy products, bets on a paradigm shift and argues that both energies satisfy different global demand markets. The direct effect between the energy market and agricultural products has been studied in Ji et al. (2018) and, also, the contagion risk between the energy market and the non-energy (commodity) market in Koirala et al. (2015) and Algieri (2017), all three studies making use of CoVar copulas method. Kang et al. (2017) examines the direction and information transmission of six commodities (gold, silver, WTI, corn, rice and wheat) by using a DECO-GARCH model and conclude that the effects intensify in the period of financial crisis and the commodities that produce more effects on the others are gold and silver.

The third branch of the literature analyses the connectivity of cryptocurrencies with other asset classes, such as the commodities. Corbet et al. (2018) studies the relationships of cryptocurrencies with other asset classes, highlighting the investment asset function of cryptocurrencies and in turn the short-term independence from market indices and commodities as the SP500 index and gold, respectively. Jareño et al. (2020) analyses the returns of Bitcoin and its sensitivity to changes in the price of gold, as well as with other international risk factors, by applying the NARDL model and conclude that Bitcoin's sensitivity is greater during periods of crisis. Bouri et al. (2018) also studies through such methodology the short- and long-term effects of BTC, aggregate output and gold price. Xiao (2020) studies the determinants of cryptocurrency returns, and highlights the sensitivity of these to changes in financial markets such as NYSE and SP500, as well as shows the sensitivity to changes in the price of gold and the information received in Forex.

Numerous studies have been conducted on whether cryptocurrencies can serve as a safe-haven, a hedge, or a diversifier for investors in comparison to traditional assets. Canh et al. (2019) examines the diversification role of leading cryptocurrencies from oil and gold price shocks and show that cryptocurrencies exhibit a useful diversification capability. The inclusion of Bitcoin in a multi-asset portfolio (with bonds, stocks, currencies, oil, real estate and gold) achieves significant diversification benefits according to Symitsi and Chalvatzis (2019). Smales (2019) highlights that Bitcoin returns are not correlated with other assets and that it shows higher volatility than gold. According to this and given hypothetical financial crisis conditions, Bitcoin is not considered as a safe-haven. A study by Charfeddine et al. (2020) documents the existence of interconnection between cryptocurrencies and conventional assets. This study demonstrates cryptocurrencies are particularly sensitive to economic, financial, and political shocks, and they can be used as diversification instruments, but they are not good hedging instruments. Peterson et al. (2020) compares eight cryptocurrencies and gold in a quantile decomposition and conclude that, in hedging other assets, cryptocurrencies and gold are both useful, and in the case of cryptocurrencies, they highlight their non-speculative function. On the other hand, Wu et al. (2019) analyses whether gold or Bitcoin are assets that act as a safe-haven in the face of uncertain economic policy (EPU), making use of a GARCH model and quantile regression. The conclusion of their model states that Bitcoin reacts more to model shocks while gold remains more stable, showing hedging endowments. Even so, they believe that both assets can serve to diversify risks and believe that Bitcoin responds positively to bull and bear markets, maintaining positive stability and certainty for investors. Papadamou et al. (2021a) also explore whether the safe-haven role of gold and the EPU index influence on some leading cryptocurrencies in a non-linear manner. Furthermore, they distinguish between bull and bear crypto markets, showing that during periods of economic turbulence cryptocurrencies are more influential. The relevance of separating between bull and bear markets in the study of the cryptocurrency markets can be seen in other recent papers such as Papadamou et al. (2021b), which focuses on analysing herd behaviour in crypto markets. Thus, its results are essential for constructing investment portfolios at different market states. In addition, Naeem et al. (2020) compares four cryptocurrencies (BTC, Ethereum, Litecoin and Ripple) together with four commodities (metals, agricultural, precious metals and energy), highlighting these cryptocurrencies are an important refuge and hedge for the commodities in their model, especially in crisis periods. Bouri et al. (2017) explores the connection between Bitcoin and commodities, assessing whether BTC has the function of a shelter in the face of changes in commodities, mainly energy since electricity is the essential instrument for Bitcoin to function. Finally, a remarkable study on the comparison between the cryptocurrency and commodities market is that of Wang et al. (2019), which focuses their study on the Chinese market using a VAR-GARCH-BEKK model to find out whether it is a safe-haven against six financial assets (including commodities). Finally, it concludes that Bitcoin is not a safe-haven against commodities and gold and in fact, in the face of market price changes, the three elements mentioned above act in parallel. On the contrary, Bitcoin is a safe asset against bonds or stocks. SARS-CoV2 has been a very influential element in both the cryptocurrency and the commodity market. Despite being a relatively new phenomenon (just a year ago), much of the literature has focused exclusively on analysing such an unusual effect as a global pandemic.

Goodell and Goutte (2021) studies Bitcoin reactions to SARS-CoV-2, as well as its evolution throughout the pandemic. It is a curious analysis because it determines that the higher the level of contagion and deaths due to the coronavirus worldwide, the higher the price of BTC, establishing a direct relationship between these aspects, with contagion being higher and, therefore, the rise in the price of Bitcoin as of April 5. Demiralay and Golitsis (2021) makes use of a dynamic GARCH model to analyse the co-movements of the cryptocurrency market before and after SARS-CoV2. They conclude that correlations between cryptocurrencies peak in March 2020, following the WHO declaration of “global pandemic”. Bitcoin trading volume and Bitcoin demand driven by risk aversion were the most important drivers of increasing correlations between cryptocurrencies.

Umar and Gubareva (2020) finds that the Coronavirus Panic Index (PI) is interconnected with the exchange rates of some currencies and cryptocurrencies. They also find that the Chinese yuan has the highest return and that it may be due to a strong central bank and more direct decision making to confront the virus.

On the other hand, the arrival of SARS-CoV2 has influenced many authors who have determined that Bitcoin or cryptocurrencies in general have ceased to be a safe security because of this fact (Umar et al., 2021c). Among them, Conlon et al. (2020) reveals that Bitcoin is not a hedge or a safe-haven during the COVID-19 period, and that a small amount towards Bitcoin in a portfolio drastically increases its risk, putting in doubt that it is an asset that protects investors during the SARS-CoV-2 period. Mariana et al. (2021) analyses whether, given the effects of SARS-CoV-2 on a global scale, Bitcoin and Ethereum continue to be a safe asset or whether, on the contrary, there is a juncture in the absence of regulation. According to the GARCH methodology used, in the short term both cryptocurrencies are a safe asset and returns are inversely related to SP500 returns. They find that Ethereum may be a safer asset than Bitcoin and that both coins have high volatility. Sifat (2021) concludes that there is independence between price, volatility and trading activities of cryptocurrencies and global indicators for financial markets from 2015 to 2021 (including the SARS-CoV-2 effect). Even if the latter period is isolated, the effects are even more conclusive. Finally, the authors affirm that cryptocurrencies should be treated as a separate asset class and as a safe-haven in the face of investor diversification.

Another approach regarding the cryptocurrency market is by Corbet et al. (2020a), consisting of reinforcing the position we saw from Conlon and McGee (2020) and further determining that a cryptocurrency asset acts as an amplifier of contagion rather than a safe-haven during times of strong financial turmoil, being a novel idea that we had not seen yet. Some months later, Corbet et al. (2020b) redirects some previous ideas, by determining that there is data that proves a significant growth of returns and traded volumes of large cryptocurrencies and therefore, they could have been a safe -haven asset for investors. Moreover, those returns were influenced by the negative sentiment of SARS-CoV-2, thus they had a diversifying role for investors, assimilating their role to that of precious metals in historical crises.

Moreover, Jiang et al. (2021), reinforces the idea that cryptocurrencies are no longer a safe-haven from stock market shocks, making use of a quantile approach to the data. It analyses up to six cryptocurrencies and six capital market indices, with Ethereum being the only cryptocurrency that acts as a risk diversifier in the short term, the rest being valid in the long term.

Alternatively, Umar et al. (2021) examines the existing connectivity and volatility in the profitability of three markets for agricultural commodities (cereals, soft commodities and livestock) and the Coronavirus Mean Coverage Index (MCI). A TVP-VAR methodology is applied and highlights a continuous fluctuation and higher connectivity during the peak of the crisis (March 2020) and subsequently higher volatility (in April 2020). After the analysis, it is concluded that grain is the commodity that is the dominant transmitter to the system. Lin et al. (2021) also makes use of the TVP-VAR methodology to analyse energy market connectivity, which increased exponentially in March 2020, although only for two months, with gasoline and WTI (crude oil) being the only ones that have changed the direction of the indirect effects, while the rest of the energy products only changed the intensity of the adjustment.

For their part, Shruthi and Ramani (2021) studies the period before the financial crisis and the period after with respect to agricultural products (wheat, corn, pulses and sugar) and oil in the Indian market. They find a greater impact of oil market volatility on agricultural commodities in the post-financial crisis period, with the exception of sugar. They believe that there are global factors such as risk in primary markets that drive short-term unpredictability, especially in countries that are unprotected against changes in food prices.

Rajput et al. (2020) analyses the effects that SARS-CoV2 has had on the price of oil and its different causes, highlighting the drastic fall in demand due to the lack of industry and travel restrictions worldwide. They also study the drop in the price of precious metals, but above all they focus their analysis on crude oil because of the effects it has on other markets. Agricultural products do not suffer from this fall as they have less impact on other economic activities that have been greatly affected.

Bongards et al. (2021) analyses the evolution of the price of 20 commodities since before March 2020 and their reaction after the financial crisis. They investigate whether there has been some sort of unconscionable overpricing with a subsequent proportional price reversal in the opposite direction. They highlight that, following the financial crisis, such overpricing and its amplitudes are more common in commodities, with “soft” and metallic commodities having lower overpricing compared to precious metals and energy commodities.

Kamden et al. (2020) constructs a different approach to analysing the predictability of future commodity prices and their model accurately predicts future commodity prices (which also includes crude oil) using a Granger causality model. It is noteworthy that his model predicts that with an increase in confirmed cases and deaths, the price of commodities will rise, and therefore he considers it to be a good parameter for investors when forecasting the future direction of commodity prices. Along the same lines, Pabuçcu et al. (2020) examines the predictability of changes in Bitcoin prices using alternative and fresh methodologies such as Machine Learning, Artificial Neural Network, among others.

In very similar terms to the above, Salisu et al. (2020) examines how the Global Fear Index (GFI) impacts commodity prices in order to be able to establish an empirical relationship and proceed to its prediction. The index takes into account all the countries and territories of the world, which makes the conclusion extensible to many countries, but we must take into account the limitations of each one. Results of their model indicate that commodity returns are directly linked to the global fear index. Furthermore, they give the role of safe haven value to commodities in this context, as e.g., stock markets have an inverse relationship with the GFI and thus cease to be a safe haven value.

Adekoya et al. (2021) analyses the losses that investors are taking due to SARS-CoV2 and thus study about which commodities are really a safe-haven value in time of uncertainty and financial crisis. They contradict some previous studies on this subject and argue that gold is a good safe-haven security in the face of the unpredictability of crude oil and stock prices.

For the period before and after the 2020 financial crisis due to SARS-CoV-2, Gonzalez et al. (2020a, 2020b) studies the performance of stock, bond and cryptocurrency portfolios. The portfolio described above is compared with another asset portfolio composed only of stocks and bonds. In principle, it appears that in the model performed cryptocurrencies control risk by not exceeding 50 basis points of the risk of the stock and bond portfolios; however, there are exceptions and cryptocurrencies that do not control risk. One example is Bitcoin, which suffered a significant drop in the month of March 2020. In their conclusions they advise a potential investor to turn to Binance and Tether as they bear the risks better, although their profitability is somewhat lower.

In addition, in the aftermath of the COVID-19 pandemic, Kwapień et al. (2021) examines the detrended cross-correlations between 80 of the most liquid cryptocurrencies listing on Binance platform and also between the cryptocurrency market and some traditional markets, like the stock markets, commodity markets, and Forex over the SARS-CoV2 pandemic period. They conclude that the cryptocurrencies become more strongly cross-correlated among themselves and also with the other markets during turbulent periods.

Moreover, Ji et al. (2020) evaluates new assets considered as safe-havens, highlighting that there are two new futures that increase their value function as a safe-haven, such as gold and soybeans, while cryptocurrencies and foreign exchange decrease their effectiveness after this analysis. Gold is always considered as an asset that maintains a stable value, while soybean surprises because it is not usually a commodity considered with this function by the economic literature. Crude oil is discarded as a safe-haven asset due to the lack of consumption and industrial sector affected by the oversupply of crude oil. Additionally, the fact that cities and countries are blocked by borders reduces international trade and affects currencies. As many countries have a deficit of food products, it is logical that these acquire greater value and weight as a safe-haven.

Thus, this paper aims to further study the effect of the coronavirus on the potential asymmetric interdependencies among the four leading cryptocurrencies and five commodities of a different nature such as gold, platinum, natural gas, corn and cotton. In addition, gold is often compared to cryptocurrencies but not platinum, natural gas, corn and cotton, as they are more atypical and belong to different markets. Therefore, this paper attempts to shed light on this issue.

3. Data and methods

3.1. Data

The main purpose of this study is to examine the asymmetric effects of the COVID-19 pandemic on the interdependence between cryptocurrency and commodity markets. Specifically, the selected cryptocurrencies have been those with the highest market cap for most part of the analysis period, that is Bitcoin (BTC), Ethereum (ETH), Tether (USDT) and Cardano (ADA). On the other hand, the commodity data used were those corresponding to platinum, gold, natural gas, corn and cotton.[1] The data have been extracted from the Investing.com website.

The study covers the period from March 1, 2018 to March 26, 2021. After data homogenization, we have 775 daily observations. The reason for choosing this sample period was to have a part of the sample prior to COVID-19, as well as another part after the pandemic declaration by the WHO on March 11, 2020. Therefore, two sub-periods are distinguished within the complete sample period in order to check for robustness of our results that will lead to the conclusions of this research. The first sample sub-period comprises data from the first two years (from March 1, 2018 to March 11, 2020), while the second sample sub-period analyses the effect of the SARS-CoV2 pandemic crisis.

For the daily log returns of the cryptocurrencies, Table 1, Panel A, (upper part) presents descriptive statistical parameters, unit root and stationarity tests. The mean of the returns is positive with the exception of Tether, which approaches a zero mean. The standard deviation shows relatively low results, ranging from 0.3% to 7.2%.

The skewness is negative for all the cryptocurrencies analysed, with higher incidence in Bitcoin (−1.40). Therefore, the values tend to gather on the right side of the mean. The kurtosis coefficient tells us the concentration of the values of a variable, according to a distribution zone. In this case, we see that the kurtosis coefficient is high for all cryptocurrencies, showing leptokurtic distributions.

With the Jarque Bera (JB) test we seek to check whether our variable has the same skewness and kurtosis characteristics as a normal distribution. As the values are higher than the JB reference value for 95% probability (5.99), the null hypothesis is rejected and, therefore, the variables are not normally distributed.

To test the stationarity of cryptocurrencies we have used the unit root (ADF y PP) and stationarity (KPSS) tests. The two-unit root tests (ADP and PP) hypothesize that the variable would not be stationary, and therefore may have a unit root y. On one hand, the KPSS stationarity test defines the null hypothesis of the stationarity of the variable. In the first two tests, all variables have a stationarity result, as the null hypothesis is not satisfied. On the other hand, the KPSS test (including trend and independent term) would accept the null hypothesis of stationarity. Therefore, the three tests confirm that the daily logarithmic returns of the analysed cryptocurrencies are non-stationary variables.

[1]The reasons for selecting these commodities in the paper are related to their evolution throughout the COVID-19 pandemic. Considering the context of paralysis of much of the world's economic activity due to the pandemic, coupled with climate change, with increasingly warmer winters, have led to an expected drop in demand for natural gas by 4% in 2020. The cotton market also came to a standstill, as the confinement caused by the pandemic prevented cotton from being harvested. The pandemic also affected corn, so we thought it would be interesting to explore its behaviour in this paper. Finally, gold and platinum commodities have been chosen as safe havens, as the financial literature has given them this role in many scenarios.

Table 1. Descriptive statistics of daily log-returns of top cryptocurrencies and a mixture of commodities.

Panel A: Descriptive statistics and classical unit-root and stationarity tests

Variables	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	JB stat.	ADF stat.	PP stat.	KPSS stat.
Bitcoin	0.0021	0.0018	0.2008	−0.4973	0.0470	−1.4078	20.6868	10344.24***	−29.4549***	−29.4169***	0.0731
Cardano	0.0018	−0.0008	0.2869	−0.5361	0.0720	−0.1330	8.2242	882.45***	−17.3225***	−28.5548***	0.0624
Ethereum	0.0009	0.0001	0.3481	−0.5896	0.0621	−0.8698	15.5413	5170.00***	−29.6799***	−29.6325***	0.0327
Tether	0.0000	0.0000	0.0208	−0.0256	0.0030	−0.2118	22.4160	12163.38***	−25.7186***	−34.6593***	0.0232
Platinum	0.0003	0.0006	0.0993	−0.1361	0.0190	−0.6449	10.6961	1,963.80***	−17.32***	−27.03***	0.1812
Gold	0.0003	0.0005	0.0561	−0.0511	0.0100	−0.0981	9.5783	1,396.82***	−29.21***	−29.80***	0.1568
Natural gas	−0.0001	−0.0007	0.1980	−0.1805	0.0341	0.3962	8.1585	878.41***	−22.65***	−29.05***	0.0630
Corn	0.0005	0.0007	0.0577	−0.0629	0.0143	0.0477	4.8775	113.97***	−26.86***	−26.86***	0.3320
Cotton	0.0000	0.0003	0.0592	−0.0485	0.0147	0.0204	4.2664	51.8***	−29.12***	−29.12***	0.2255

Panel B: Zivot and Andrews (1992) sequential test for a unit root and BDS non-linearity test

Tests	Bitcoin	Cardano	Ethereum	Tether	Platinum	Gold	Natural Gas	Corn	Cotton
ZA	−15.153***	−17.826*	−14.632**	−14.698***	−14.663***	−14.878**	−22.919***	−27.219***	−29.483***
BDS	0.0349***	0.0354***	0.0248***	0.1633***	0.0442***	0.0467***	0.0614***	0.0286***	0.0233***

Notes: A summary of the most relevant descriptive statistics can be found in this table. The following abbreviations are used: max. (maximum value), min. (minimum value), Std. Dev. (Standard Deviation), JB stat. (Jarque-Bera test for normality). The ADF (Augmented Dickey-Fuller) and PP (Phillips-Perron) unit root tests, and KPSS (Kwiatkowski et al.) stationarity test are collected. The results of the Zivot and Andrews (1992) sequential test for a unit root with the alternative hypothesis of stationarity and a single structural change in the deterministic trend are also reported in the table as ZA. BDS (Brock et al., 1996) tests non-linearity of the explained variable using the bootstrap procedure (with 5000 repetitions), dimension four and value 0.7 to obtain probabilities. The statistical significance levels are 10%, 5%, and 1% for *, **, and ***, respectively.

In turn, Table 1, Panel A (lower part) displays several descriptive statistics of the log returns of the commodities examined in this study. Similar to the above, the mean data for the five variables are close to zero, with a negative mean only in the case of natural gas.Likewise, the standard deviation of commodities (around 1% in all cases) is much lower compared to the resulting standard deviations in cryptocurrency returns. The skewness is negative in the platinum and gold variables; hence their values tend to lie to the right of the mean. On the contrary, the rest of the variables have positive skewness and most of their values lie to the left of the mean.

The kurtosis coefficient has a lower value than that established for cryptocurrencies; however, all commodities have a leptokurtic distribution, although corn and cotton are the variables most associated with a normal distribution as they have lower values. The null hypothesis of the Jarque-Bera (JB) test is not satisfied for any variable and, therefore, none of them follow a normal distribution. As in the previous case, corn and cotton have the lowest JB test, so their distributions are closer than the rest to a normal distribution.

The unit-root (ADF, PP) and the stationarity (KPSS) tests show that the variables are stationary, as the first two do not fulfill the null hypothesis in any of the variables and the null hypothesis of the KPSS is fulfilled in all the variables, so we can conclude that all of them are stationary variables.

Lastly, to test potential structural breaks, happen due to political events and policy changes, even economic events, the Zivot and Andrews (1992) test is collected in Table 1, Panel B. Thus, this sequential test for a unit root rejects the null hypothesis for all the variables analysed. In addition, to validate the suitability of applying the NARDL model, the BDS independence test (Brock et al., 1996) is obtained. Regarding the BDS independence test for checking a variety of possible deviations from independence (linear dependence, non-linear dependence, chaos, etc.), the non-linearity of the explained variables justifies the use of an alternative estimate procedure, such as the NARDL approach. All variables confirm the non-linearity of the series.

3.2. Methods

This sub-section of the paper presents the model selected to study the asymmetric interdependencies between the four leading cryptocurrencies and five commodies' returns, focusing on the possible effect that the COVID-19 pandemic may have on such connectedness. Thus, we start from a nonlinear autoregressive distributed lag model (henceforth, NARDL) that was developed by Shin et al. (2014) based on an earlier non-asymmetric model built by Pesaran and Shin (1999).

Throughout the previous section, we have mentioned some of the most commonly used techniques in the financial literature such as Quantile Regression (QR), GARCH model (Generalized AutoRegressive Conditional Heteroscedasticity)[2], SVAR model (Structural Autoregressive Variables Model), linear Granger causality model, CoVaR copulas method (variant of QR), and even making use of several previous models such as the VAR-GARCH-BEKK model and the TVP-VAR methodology. But there are undoubtedly many other frequently used methodologies that have not been mentioned, including, among others, Ordinary Least Squares (OLS) and the SUR (Seemingly Unrelated Regression) approach.

The purpose of some of the previous methodologies is the estimation in the short and long-term considering a series of symmetrical relationships between variables (symmetry is assumed in the models). However, the NARDL methodology is used to be able to estimate in the short and long-term but considering possible asymmetries of the variables that the model itself predicts.

Arize et al. (2017) and Jareño et al. (2019, 2021) expose some of the possibilities offered by this methodology. Specifically, it allows us to check that the time series have nonlinear cointegration. By

[2]Please, see Gyamerah (2019) for further discussion on the suitability of using the GARCH methodology to model cryptocurrency market volatility.

decomposing partial sums of regressors into both positive and negative, we can simultaneously check for nonlinearity in the short and long run. With this methodology, we can also separately measure the contributions of the asymmetric dynamic multipliers to adjustments in both signs in the regressors.

The previous authors also highlight other advantages of this methodology, such as considering that it is an adequate technique for small samples, without forcing the variables to be stationary. As mentioned above, it also provides us with estimates of coefficients in the short and long term. Unlike other methods, NARDL has no correlation between its residuals, so lag bias is not at risk when using the methodology.

In order to perform an empirical estimation of the NARDL methodology, an analysis of stationarity of the variables is required by applying the classical stationarity and unit root tests. Based on these tests, it appears that there is a stationary distribution for all variables.

We apply partial-sum decompositions to calculate asymmetric cointegration on the basis of the returns of four selected cryptocurrencies and six commodities:

$$R_{jt} = \alpha_2 + \alpha^+ \cdot G_t^+ + \alpha^- \cdot G_t^- + \varepsilon_{jt} \tag{1}$$

$$\Delta G_t = v_{2t} \tag{2}$$

$$R_{jt} = \alpha_1 + \alpha^+ \cdot P_t^+ + \alpha^- \cdot P_t^- + \varepsilon_{jt} \tag{3}$$

$$\Delta P_t = v_{1t} \tag{4}$$

$$R_{jt} = \alpha_3 + \alpha^+ \cdot NG_t^+ + \alpha^- \cdot NG_t^- + \varepsilon_{jt} \tag{5}$$

$$\Delta NG_t = v_{3t} \tag{6}$$

$$R_{jt} = \alpha_3 + \alpha^+ \cdot C_t^+ + \alpha^- \cdot C_t^- + \varepsilon_{jt} \tag{7}$$

$$\Delta C_t = v_{3t} \tag{8}$$

$$R_{jt} = \alpha_3 + \alpha^+ \cdot Cot_t^+ + \alpha^- \cdot Cot_t^- + \varepsilon_{jt} \tag{9}$$

$$\Delta Cot_t = v_{3t} \tag{10}$$

where R_{jt}, G_t, P_t, NG_t, C_t and Cot_t are scalar I(1) variables. In particular, R_{jt} are the returns of the four leading cryptocurrencies in *t*, G_t is the Gold returns in *t,* where G_t^+ and G_t^- are partial sums of positive and negative changes in Gold returns, and the same for Platinum, P_t, Natural Gas, NG_t, Corn, C_t, and Cotton, Cot_t. ε_{jt} y v_t are random shocks and $\alpha = (\alpha_0, \alpha^+, \alpha^-)$ is an estimation vector for long-run parameters. Finally, α^+ and α^- are coefficients that describe long-run interconnections between the returns of the four major cryptocurrencies and increments (α^+) or reductions (α^-), respectively, in returns from the commodities included in this research.

$$G_t^+ = \sum_{i=1}^{t} \Delta G_i^+ = \sum_{i=1}^{t} \max(\Delta G_i, 0) \tag{11}$$

$$G_t^- = \sum_{i=1}^{t} \Delta G_i^- = \sum_{i=1}^{t} \min(\Delta G_i, 0) \tag{12}$$

$$P_t^+ = \sum_{i=1}^{t} \Delta P_i^+ = \sum_{i=1}^{t} \max(\Delta P_i, 0) \tag{13}$$

$$P_t^- = \sum_{i=1}^{t} \Delta P_i^- = \sum_{i=1}^{t} \min(\Delta P_i, 0) \tag{14}$$

$$NG_t^+ = \sum_{i=1}^{t} \Delta NG_i^+ = \sum_{i=1}^{t} \max(\Delta NG_i, 0) \tag{15}$$

$$\mathrm{NG}_t^- = \sum_{i=1}^{t} \Delta\mathrm{NG}_i^- = \sum_{i=1}^{t} \min(\Delta\mathrm{NG}_i, 0) \tag{16}$$

$$\mathrm{C}_t^+ = \sum_{i=1}^{t} \Delta\mathrm{C}_i^+ = \sum_{i=1}^{t} \max(\Delta\mathrm{C}_i, 0) \tag{17}$$

$$\mathrm{C}_t^- = \sum_{i=1}^{t} \Delta\mathrm{C}_i^- = \sum_{i=1}^{t} \min(\Delta\mathrm{C}_i, 0) \tag{18}$$

$$\mathrm{Cot}_t^+ = \sum_{i=1}^{t} \Delta\mathrm{Cot}_i^+ = \sum_{i=1}^{t} \max(\Delta\mathrm{Cot}_i, 0) \tag{19}$$

$$\mathrm{Cot}_t^- = \sum_{i=1}^{t} \Delta\mathrm{Cot}_i^- = \sum_{i=1}^{t} \min(\Delta\mathrm{Cot}_i, 0) \tag{20}$$

Based on previous studies, such as Pesaran and Shin (1999), Pesaran et al. (2001), Shin et al. (2014) and Jareño et al. (2019, 2021), among others, this paper explores the connectedness between the returns of the commodities selected in this study and the cryptocurrency market in a NARDL framework:

$$R_{jt} = \beta_0 + \beta_1 \cdot R_{t-1} + \beta_2 \cdot G_t^+ + \beta_3 \cdot G_t^- + \beta_4 \cdot P_t^+ + \beta_5 \cdot P_t^- + \beta_6 \cdot NG_t^+ + \beta_7 \cdot NG_t^- + \beta_8 \cdot C_t^+ + \beta_9 \cdot C_t^- + \beta_{10} \cdot Cot_t^+ + \beta_{11} \cdot Cot_t^- + \sum_{i=1}^{p} \phi_i R_{t-i} + \sum_{i=0}^{q} (\gamma_i^+ \Delta G_{t-i}^+ + \gamma_i^- \Delta G_{t-i}^- + \gamma_i^+ \Delta P_{t-i}^+ + \gamma_i^- \Delta P_{t-i}^- + \gamma_i^+ \Delta NG_{t-i}^+ + \gamma_i^- \Delta NG_{t-i}^- + \gamma_i^+ \Delta C_{t-i}^+ + \gamma_i^- \Delta C_{t-i}^- + \gamma_i^+ \Delta Cot_{t-i}^+ + \gamma_i^- \Delta Cot_{t-i}^-) + \varepsilon_{jt} \tag{22}$$

where ϕ_i is the autoregressive parameter, the dependent variable lags p times and the regressors, q times, γ_i^+ y γ_i^- are parameters of asymmetrically distributed lags. In ε_{jt}, the mean is zero and the variance is constant.

By examining these parameters, $\sum_{i=0}^{q} \gamma_i^+$ and $\sum_{i=0}^{q} \gamma_i^-$ the short-term impact of increases and decreases in commodity returns is examined on the performance of the major cryptocurrencies in the market. Thus, this study considers both the long-term and short-term asymmetry of commodity returns.

Stepwise regression along with the error correction model will be used to estimate the proposed NARDL model, in line with Jareño et al. (2020, 2021). In addition, the latter approach allows the NARDL model to perform better in small samples and strengthens the cointegration tests.

4. Empirical results

The purpose of this section is to summarize the findings of the analysis of the connections between the four most relevant cryptocurrencies (Bitcoin (BTC), Ethereum (ETH), Cardano (ADA) and Tether (USDT)), and the returns of five commodities of different nature: gold, platinum, natural gas, corn and cotton.

Specifically, asymmetry and cointegration have been studied in the relation between the returns of the four cryptocurrencies and the five commodities using the NARDL model for daily frequency in a sample period spanning from March 1, 2018 to March 26, 2021. In addition, two sub-periods have been explored to test the robustness of the results in relation to the COVID-19 pandemic on the connectedness between these financial variables. The first sub-period (pre-COVID) runs from March 1, 2018 to March 11, 2020, the latter being the date on which the World Health Organization (WHO) declared the SARS-CoV-2 pandemic. The second sub-period (COVID) captures the health crisis experienced since the global pandemic declaration and runs from March 12, 2020 to March 26, 2021.

4.1. NARDL results for the entire sample period

Detailed results of the NARDL model as well as the tests for asymmetry and cointegration are shown in Table 2, between returns for Bitcoin, Ethereum, Cardano, and Tether and the commodities returns for the entire sample period (March 1, 2018 to March 26, 2021). Each panel contains the information of each cryptocurrency with respect to the five commodities returns.

All the tables collected in this section present the following structure for all the panels corresponding to each cryptocurrency. The PCorr (Pearson's correlation coefficient) value is displayed in column 2. Column 3 contains the Wald F test to study the cointegration (Coint) between the cryptocurrencies and the commodities. Column 4 contains the cointegration equation between these variables and represents the existing equilibrium relationship between cryptocurrencies returns and commodities returns (Eq.). As shown in column 5, a Wald test is used to determine long-term symmetry (LAsym). To check for short-term symmetry (SAsym), another Wald test is carried out as displayed in column 6. Columns 7 and 8 show, respectively, the effects of the total amount for positive and negative variations ($Lags^+$ and $Lags^-$) in the returns of each commodity analysed for (1-4) lags on the returns of the four cryptocurrencies. In the final column 9, we find the adjusted R^2 coefficient for each cryptocurrency.

Table 2, relative to the whole sample period, reveals the following results. As can be seen in column 2, Pearson's correlation coefficients reject the null hypothesis (H_0: PCorr = 0) of no correlation, in the case of gold, platinum and cotton, for all cryptocurrencies with the exception of Tether. Thus, Bitcoin, Ethereum and Cardano show statistically significant correlation with these commodities returns. In addition, gold, platinum and cotton returns are positively and statistically significantly correlated with Bitcoin, Ethereum and Cardano, with Pearson's correlation coefficients between 7.78% (cotton for Cardano) and 24.49% (platinum for Bitcoin). In contrast, all the cryptocurrencies are uncorrelated with the commodity natural gas, except for Tether that is negatively and statistically significantly correlated at the 1% level. Meanwhile, in the case of corn, the null hypothesis is rejected by Bitcoin and Ethereum at a 5% significance level.

The presence of cointegration, column 3, is evaluated with the Wald F test, by rejecting the no cointegration null hypothesis (H_0: $\beta1 = \beta2 = \beta3 = 0$) by all cryptocurrencies (with the exception of Tether) for all commodities. Therefore, this Wald F test confirms that fluctuations in gold, platinum, natural gas, corn and cotton commodities returns are cointegrated with Bitcoin, Ethereum and Cardano returns for the full period. For these three cryptocurrencies, the cointegration coefficients of variations in all commodities returns are also positive. Additionally, in the case of natural gas, the null hypothesis is rejected by all cryptocurrencies. Natural gas returns and cryptocurrencies returns for the full period are therefore cointegrated.

Table 2. NARDL results for exploring interdependencies between top four cryptocurrencies and five leading commodities returns: whole sample period (March 7, 2018–March 26, 2021).

Commodities	PCorr	Coint	Eq	LAsym	SAsym	Lags $^+$	Lags $^-$	Adj. R^2
Panel A: Bitcoin								
Gold	0.1558***	6.5133***	e^+: −9.2247*** e^-: −9.1763***	3.2863*	3.0949***	–	–	0.0375
Platinum	0.2449***	6.9130***	e+: −8.1459*** e^-: −8.0382***	1.5899	6.8990***	–	(2) 0.1578* (3) 0.2169** (4) −0.1927**	0.0900
Natural Gas	−0.0036	4.6623***	e+: −0.1605 e^-: −0.1443	3.8694**	–	–	(2) 0.1362** (3) 0.1815***	0.0231
Corn	0.0900**	3.4531**	e+: −2.0300 e^-: −1.9953	2.7483*	2.0657**	(1) 0.3674**	–	0.0213
Cotton	0.0821**	5.1264***	e+: 3.9705** e^-: 4.0105**	2.5037	–	–	–	0.0194
Panel B: Ethereum								
Gold	0.1109***	4.6139***	e^+: −7.3308** e^-: −7.2742*	3.2945*	2.6985***	–	–	0.0319
Platinum	0.2192***	7.8022***	e+: −11.0640*** e^-: −10.9433***	1.9809	6.3325***	–	(1) −0.3330**	0.0728
Natural Gas	0.0086	4.2717***	e+: 0.3511 e^-: 0.3706	3.7224*	–	(4) 0.2445***	(2) 0.1860** (3) 0.2259***	0.0331
Corn	0.0742**	3.5534**	e+: −2.2854 e^-: −2.2433	3.0473*	1.6352	(1) 0.4428*	–	0.0275
Cotton	0.0908**	3.3897**	e+: 0.0552 e^-: 0.1028	2.7984*	2.3240**	–	–	0.0312
Panel C: Cardano								
Gold	0.0731**	3.9609***	e^+: −9.3691 e^-: −9.2301	1.3129	1.6939*	–	(3) 0.6763**	0.0325
Platinum	0.2023***	4.4111***	e+: −17.6019** e^-: −17.2776**	0.4197	5.3523***	–	(4) −0.4043***	0.0742
Natural Gas	0.0110	3.7030**	e+: 1.1910 e^-: 1.2501	0.9822	–	–	–	0.0270
Corn	0.0496	3.1688**	e+: −3.1888 e^-: −3.0552	0.9056	–	–	–	0.0249
Cotton	0.0778**	3.3015**	e+: −4.5983 e^-: −4.4803	0.9984	1.6954*	–	–	0.0274

Continued on next page

Commodities	PCorr	Coint	Eq	LAsym	SAsym	Lags $^{+}$	Lags $^{-}$	Adj. R^2
Panel D: Tether								
Gold	0.0007	0.8964	e^{+}: 0.0057 e^{-}: 0.0062	0.0911	−	(2) −0.0220**	−	0.0627
Platinum	−0.0048	1.1224	e+: −0.0874 e^{-}: −0.0873	0.0023	−	−	−	0.0604
Natural Gas	−0.1063***	2.7953**	e+: 0.2548*** e^{-}: 0.2547***	0.0516	−4.0565***	−	(2) 0.0070**	0.0824
Corn	−0.0346	0.7248	e+: −0.0392 e^{-}: −0.0392	0.0006	−	(1) 0.0189*	−	0.0651
Cotton	−0.0256	0.9710	e+: −0.0742 e^{-}: −0.0742	0.0045	−	−	−	0.0598

Notes: NARDL estimates on interdependencies between cryptocurrency and commodity returns are collected in this table. The **PCorr** statistic is defined by the null of PCorr = 0 as the Pearson correlation coefficient. **Coint** is a Wald test for cointegration defined as $\beta_1 = \beta_2 = \beta_3 = 0$. This equation (**Eq**) demonstrates long-term elasticities between cryptocurrency and commodity returns (Com): $R_{jt-i} = e^{+} \cdot Com^{+}_{t-i} + e^{-} \cdot Com^{-}_{t-i}$. **LAsym** is the Wald test for the long-term symmetry null defined as $-\beta_2/\beta_1 = -\beta_3/\beta_1$. In terms of short-run symmetry, **SAsym** is Wald's test for the null if $\gamma_i^{+} = \gamma_i^{-}$. The impact of the cumulative positive and negative variations in commodity returns for ()-lags on the top four cryptocurrency returns are shown by **Lags** $^{+}$ and **Lags** $^{-}$, respectively.
The statistical significance levels are 10%, 5%, and 1% for *, **, and ***, respectively. For small samples, critical values by Narayan (2005) are used.

The cointegration equation between the commodities and the four cryptocurrencies returns, shown in column 4, shows that positive and negative changes in the returns of commodities have the same effect on the prices of all cryptocurrencies. In the case of gold, the coefficients are positive and low for Tether, while they are negative and high in absolute terms for the rest of the cryptocurrencies. In the case of platinum, the analysis is similar, but the coefficients of Tether are also negative. In this case, Bitcoin and Ethereum reflect a significance level of 1% and Cardano 5%. In the case of natural gas, just Tether is statistically significant at the 1% level. As regards corn, no cryptocurrency is statistically significant. Finally, in the commodity cotton, the only statistically significant cryptocurrency is Bitcoin at the 5% level.

For gold, natural gas and corn, Bitcoin and Ethereum reject the null hypothesis of long-term symmetry (H_0: $-\beta 2/\beta 1 = -\beta 3/\beta 1$). Ethereum rejects the null hypothesis as well for cotton. At 5% and 10% levels, all statistically significant coefficients are positive, also showing some evidence of long-term asymmetry between the variables mentioned above. Finally, the long-run null hypothesis for any commodity is not rejected by Cardano and Tether, thus showing no signs of evidence of asymmetry in long-term effects.

All cryptocurrencies reject the short-term symmetry null hypothesis (column 6) (H_0: $\gamma_i^{+} = \gamma_i^{-}$), except Tether, in the analysis of gold and platinum. Both commodities show positive and statistically significant coefficients at the 1% level (except for Cardano and gold, for which the level is 10%). Accordingly, Bitcoin, Ethereum, and Cardano tend to have asymmetric short-term reactions to changes in gold and platinum returns for the entire sample period. Contrarily, in the case of natural gas, the null hypothesis is rejected just by Tether, showing a negative and statistically significant coefficient at 1%.

In the case of corn, just Bitcoin rejects the null hypothesis, with a positive and statistically significant coefficient at 5%. Finally, in the case of cotton, the null hypothesis is rejected by Ethereum and Cardano with a positive and statistically significant coefficient at 5% and 10%, respectively.

In columns 7 and 8, we collect the cumulative effects of the positive and negative variations in commodity returns, for each of the four lags on the performance of the four major cryptocurrencies. Gold is negatively affected by the cumulative sum of positive gold returns for Tether on a two lag basis, but negatively affected by the cumulative sum of negative gold returns for Cardano on a three lag basis. Cumulative negative changes in platinum returns would negatively and statistically significantly influence Bitcoin, Ethereum and Cardano returns for 4-, 1-, and 4- lags, respectively. Contrarily, this impact is positive on Bitcoin returns for 2- and 3-lags. Using 4-lag returns for the commodity natural gas, we find a measurable effect of the cumulative positive fluctuations in the commodity on the returns for Ethereum. However, cumulative negative changes in natural gas returns would positively and statistically significantly affect returns for Bitcoin (2- and 3-lags), Ethereum (2- and 3-lags) and Tether (2-lags). For 1 lag, cumulative positive fluctuations in corn returns may exhibit a positive and statistically significant influence for Bitcoin, Ethereum and Tether returns. Finally, in the case of cotton, there are no effects for any cryptocurrencies. Despite this last result, cumulative changes in commodity returns (except cotton), whether positive or negative, possess persistent effects, for the returns of most cryptocurrencies.

Lastly, we discuss the NARDL model's explanatory power, shown in column 9 through the adjusted R^2 of the model, which varies, in the case of gold, from 3.19% for Ethereum to 6.27% for Tether. In the case of platinum, the adjusted R^2 varies from 6.04% for Tether to 9% for Bitcoin. Likewise, in the commodity natural gas it varies from 2.31% for Bitcoin to 8.24% for Tether and in the case of corn it varies from 2.13% for Bitcoin to 6.51% for Tether. Finally, in the case of the commodity cotton, Tether's explanatory power is 5.98%, Bitcoin's is 1.94%.

4.2. NARDL results for the pre-COVID-19 sub-period

On Table 3, we show detailed results of the NARDL model as well as the tests for asymmetry and cointegration between returns for Bitcoin, Ethereum, Cardano, and Tether and the commodities returns for the pre-COVID sub-period (March 1, 2018–March 11, 2020). In turn, the table includes panels containing information on the returns of each cryptocurrency relative to the five commodity returns with the same organisation as Table 2.

Regarding the correlation between commodities returns and cryptocurrencies returns (column 2), in the case of gold, only Bitcoin rejects the null hypothesis, and concretely it is positively and statistically significantly correlated with gold returns, at 10% significance level. On the other hand, in the case of platinum, corn and cotton, any cryptocurrency rejects the no correlation null hypothesis. Finally, as regards natural gas, the null hypothesis is just rejected by Tether, being negatively and statistically significantly correlated at 1%.

Table 3. NARDL results for exploring interdependencies between top four cryptocurrencies and five leading commodities returns: **Pre-COVID sub-period** (March 7, 2018–March 11, 2020).

Commodities	PCorr	Coint	Eq	LAsym	SAsym	Lags $^{+}$	Lags $^{-}$	Adj. R^2
Panel A: Bitcoin								
Gold	0.0835*	0.6963	e^{+}: 28.5661 e^{-}: 28.3737	0.0629	2.0534**	–	(3) 0.5364*	0.0085
Platinum	0.0541	0.5675	$e+$: −7.9463 e^{-}: −8.1639	0.1355	1.8501*	–	(4) −0.3492**	0.0148
Natural Gas	−0.0340	0.7456	$e+$: −10.1858 e^{-}: −10.4654	0.0077	–	–	(2) 0.1910*** (3) 0.1554**	0.0155
Corn	0.0233	0.3935	$e+$: 3.2789* e^{-}: 3.2093*	0.1724	–	(1) 0.3953**	–	0.0111
Cotton	−0.0119	1.6670	$e+$: −16.1106* e^{-}: −16.2295*	0.1094	–	–	–	0.0039
Panel B: Ethereum								
Gold	00160	0.7482	e^{+}: −39.3882 e^{-}: −40.7911	0.0093	–	–	(3) 0.9095**	0.0118
Platinum	0.0531	0.6984	$e+$: −16.9829 e^{-}: −18.4299	0.0145	2.1627**	–	(4) −0.4342**	0.0158
Natural Gas	−0.0572	2.4292*	$e+$: −172.9252* e^{-}: −174.9419**	0.0005	–	–	(2) 0.2024**	0.0152
Corn	0.0266	0.6865	$e+$: 12.9284 e^{-}: 12.5638	0.0348	–	(1) 0.5614**	–	0.0160
Cotton	−0.0155	2.0933	$e+$: −212.8352* e^{-}: −214.9056*	0.0013	–	–	–	0.0064
Panel C: Cardano								
Gold	−0.0058	0.4828	e^{+}: −1.5143 e^{-}: −1.6128	0.3290	–	–	(3) 1.0955***	0.0121
Platinum	0.0252	0.3016	$e+$: −2.2050 e^{-}: −2.3400	0.2001	1.7983*	–	(4) −0.5271**	0.0138
Natural Gas	−0.0484	0.9273	$e+$: −4.5583 e^{-}: −4.6110	0.2169	–	–	(2) 0.2119** (3) 0.2013*	0.0140
Corn	−0.0115	0.5190	$e+$: 0.5966 e^{-}: 0.5495	0.3388	–	(1) 0.6508**	–	0.0115
Cotton	0.0002	0.8065	$e+$: −5.9295 e^{-}: −5.9919	0.3153	–	–	–	0.0031

Continued on next page

Commodities	PCorr	Coint	Eq	LAsym	SAsym	Lags $^{+}$	Lags $^{-}$	Adj. R^2
Panel D: Tether								
Gold	−0.0270	0.8614	e^{+}: 0.7571 e^{-}: 0.7600	0.1736	–	–	(1) 0.0672^{**}	0.0614
Platinum	−0.0037	0.5585	$e+$: −0.2013 e^{-}: −0.1995	0.0501	–	–	–	0.0544
Natural Gas	-0.1385^{***}	3.0734^{**}	$e+$: 0.7201^{***} e^{-}: 0.07197^{***}	0.4464	-4.5577^{***}	–	–	0.0916
Corn	−0.0380	0.2599	$e+$: 0.0909 e^{-}: 0.0912	0.0058	–	(1) 0.0370^{**}	–	0.0652
Cotton	−0.0239	0.4276	$e+$: −0.1046 e^{-}: −0.1040	0.0378	–	–	–	0.0537

Notes: NARDL estimates on interdependencies between cryptocurrency and commodity returns are collected in this table. The **PCorr** statistic is defined by the null of PCorr = 0 as the Pearson correlation coefficient. **Coint** is a Wald test for cointegration defined as $\beta_1 = \beta_2 = \beta_3 = 0$. This equation (**Eq**) demonstrates long-term elasticities between cryptocurrency and commodity returns (Com): $R_{jt-i} = e^{+}\cdot Com^{+}_{t-i} + e^{-}\cdot Com^{-}_{t-i}$. **LAsym** is the Wald test for the long-term symmetry null defined as $-\beta_2/\beta_1 = -\beta_3/\beta_1$. In terms of short-run symmetry, **SAsym** is Wald's test for the null if $\gamma_i^{+} = \gamma_i^{-}$. The impact of the cumulative positive and negative variations in commodity returns for ()-lags on the top four cryptocurrency returns are shown by **Lags** $^{+}$ and **Lags** $^{-}$, respectively.

The statistical significance levels are 10%, 5%, and 1% for *, **, and ***, respectively. For small samples, critical values by Narayan (2005) are used.

As far as the existence of cointegration (column 3) is concerned, there is no cointegration between changes in the returns of cryptocurrencies and the returns of the commodities gold, platinum, corn and cotton. In contrast¸ in the case of natural gas, the null hypothesis is rejected by Ethereum and Tether, at a significance level of 10% and 5% respectively.

The cointegration equation between commodities returns and the returns of the four cryptocurrencies, collected in column 4, shows that positive and negative changes in commodity returns affect the returns of all cryptocurrencies in the same way. In the case of gold and platinum, any cryptocurrency's long-run elasticity is not statistically significant in terms of the positive and negative cumulative changes in returns. On the other hand, corn and cotton show statistically significant long-term elasticities for Bitcoin at a 10% significance level and just for Ethereum in the case of cotton. Finally, natural gas exhibits statistically significant elasticities for Ethereum and Tether at 5% and 1% significance level, respectively. Moreover, low positive coefficients are found for Tether, while high negative coefficients for Ethereum.

In column 5, Wald test results show that no cryptocurrency rejects the long-tern symmetry null hypothesis. Hence, no commodity may have a long-term asymmetric effect on any cryptocurrency.

However, the Wald test to study short-term symmetry, column 6, evidences that for the commodity gold, only Bitcoin rejects the short-term symmetry null hypothesis at a 5% significance level. In the case of platinum, Bitcoin, Ethereum and Cardano reject the null hypothesis (Bitcoin and Cardano at a 10% significance level and Ethereum at 5%). Finally, for the commodity natural gas, Tether rejects the null hypothesis, showing a negative and statistically significant coefficient at 1% level. Therefore, Bitcoin responds asymmetrically, in the short-term, to changes in gold and platinum returns; Cardano and Ethereum react similarly to variations in platinum returns, while Tether reacts to natural gas fluctuations.

Regarding the impact of the cumulative positive and negative variations in commodities returns, between 1- and 4- lags, for the four leading cryptocurrencies returns (columns 7 and 8), there is a statistically significant effect of the cumulative positive fluctuations in corn returns may exhibit positive and statistically significant impact on all cryptocurrencies returns for 1-lag. However, the negative cumulative variations in gold returns would have positive and statistically significant effects for all cryptocurrencies returns for 3 lags, except for Tether with 1 lag. Likewise, negative cumulative fluctuations in platinum returns may have negative and statistically significant effects for all cryptocurrencies returns for 4-lags, except Tether, which has no effect. In the case of natural gas, negative cumulative oscillations in the performance of natural gas would have a positive and statistically significant impact on Bitcoin returns for 2- and 3- lags; on Ethereum for 2-lags and on Cardano for 2- and 3-lags. However, in the case of corn and cotton, there are no effects of the negative cumulative variations in corn and cotton returns for all cryptocurrencies returns. Therefore, the cumulative positive and negative variations, mainly in the returns of gold, platinum and natural gas, have greater persistent effects for Bitcoin, Ethereum and Cardano in the yields of the selected commodities with respect to the yields of cryptocurrencies depends on the commodity analysed, finding greater persistence in the cryptocurrencies Bitcoin, Ethereum and Cardano.

Lastly, the adjusted R^2 of the NARDL models varies, in the case of gold, from 0.85% for Bitcoin to 6.14% for Tether. In the platinum commodity, it varies from 1.38% for Cardano to 5.44% for Tether. The natural gas results vary from 1.40% for Cardano to 9.16% for Tether. Commodity corn reflects results ranging from 1.11% for Bitcoin to 6.52% for Tether. Finally, cotton shows results ranging from 0.31% for Cardano to 5.37% for Tether. In the cases of platinum, corn and cotton, the explanatory power of Bitcoin, Ethereum and Cardano is lower than in the full period

4.3. NARDL results for the COVID-19 sub-period

The NARDL regression results and the asymmetry and cointegration tests between cryptocurrency and commodities returns during the COVID sub-period (from March 12, 2020 to March 26, 2021) are shown in Table 4.

Bitcoin, Ethereum and Cardano rejects the no correlation null hypothesis (column 2) for all commodities except for natural gas. Thus, gold, platinum, corn and cotton returns are positively correlated with Bitcoin, Ethereum and Cardano returns. Moreover, correlation values vary between 39% for Bitcoin, in the case of platinum, and 12.43% for Cardano, in the case of corn, and these coefficients are higher during the pandemic sub-period than in the other periods previously analysed. In addition, gold returns are positively correlated with Tether returns.

Table 4. NARDL results for exploring interdependencies between top four cryptocurrencies and five leading commodities returns: **COVID sub-period** (March 12, 2020–March 26, 2021).

Commodities	PCorr	Coint	Eq	LAsym	SAsym	Lags $^{+}$	Lags $^{-}$	Adj. R^2
Panel A: Bitcoin								
Gold	0.2246^{***}	7.0022^{***}	e^{+}: 5.1695^{***} e^{-}: 5.1178^{***}	3.0416^{*}	3.0939^{***}	–	–	0.0999
Platinum	0.3900^{***}	7.9944^{***}	$e+$: -4.4853^{***} e^{-}: -4.4469^{***}	1.1982	6.7306^{***}	–	(3) 0.2696^{**}	0.1936
Natural Gas	0.0237	3.8116^{**}	$e+$: -0.2702 e^{-}: -0.2562	1.8956	–	–	–	0.0391
Corn	0.1797^{***}	4.2560^{***}	$e+$: -3.0872^{*} e^{-}: -3.0527^{*}	1.0540^{*}	1.7000^{*}	–	–	0.0572
Cotton	0.1980^{***}	3.0031^{**}	$e+$: -1.0648 e^{-}: -1.0155	1.7664	2.6744^{***}	–	–	0.0637
Panel B: Ethereum								
Gold	0.1989^{***}	7.2467^{***}	e^{+}: -9.3267^{***} e^{-}: -9.2514^{***}	2.7547^{*}	2.5373^{**}	–	(1) -1.0737^{**}	0.0798
Platinum	0.3458^{***}	5.5029^{***}	$e+$: -4.4930^{***} e^{-}: -4.4667^{***}	0.3659	5.8105^{***}	–	(3) 0.3824^{**}	0.1608
Natural Gas	0.0732	3.4242^{**}	$e+$: -0.5347 e^{-}: -0.5185	1.3436	–	(4) 0.2523^{*}	(4) 0.2276^{*}	0.0367
Corn	0.1354^{**}	3.4165^{**}	$e+$: -2.1429 e^{-}: -2.1033	0.8056	1.9779^{**}	–	–	0.0329
Cotton	0.2232^{***}	3.9667^{***}	$e+$: -5.3615^{**} e^{-}: -5.3243^{**}	0.7054	2.6586^{***}	–	–	0.0638
Panel C: Cardano								
Gold	0.1435^{**}	1.4291	e^{+}: 11.8006^{**} e^{-}: 11.6689^{**}	0.6757	2.1856^{**}	–	(1) -1.1915^{*}	0.0530
Platinum	0.3293^{***}	3.7008^{**}	$e+$: -7.7954^{***} e^{-}: -7.7330^{***}	0.5019	5.2525^{***}	–	(3) 0.3374^{*}	0.1335
Natural Gas	0.0653	2.2005^{*}	$e+$: -1.9699 e^{-}: -1.9341	1.3459	2.0133^{**}	–	–	0.0435
Corn	0.1243^{**}	1.8005	$e+$: 2.7115 e^{-}: 2.8319	1.2601	–	(2) -0.7203^{*}	–	0.0407
Cotton	0.1657^{***}	3.4926^{***}	$e+$: -7.9167^{**} e^{-}: -7.8349^{**}	1.2687	3.2639^{***}	–	–	0.0666

Continued on next page

Commodities	PCorr	Coint	Eq	LAsym	SAsym	Lags $^{+}$	Lags $^{-}$	Adj. R^2
Panel D: Tether								
Gold	0.1120^{*}	1.8330^{***}	e^{+}: 0.0048 e^{-}: 0.0050	0.2554	–	–	–	0.1946
Platinum	−0.0161	1.6124^{***}	e+: −0.0090 e^{-}: −0.0088	0.5072	-2.4438^{**}	(2) -0.0063^{**}	(1) -0.0055^{**} (3) -0.0077^{***}	0.2466
Natural Gas	−0.0848	1.8833^{***}	e+: −0.0037 e^{-}: −0.0036	0.4464	-1.8502^{*}	–	(1) -0.0053^{***}	0.2239
Corn	−0.0391	2.1999^{***}	e+: -0.0331^{***} e^{-}: -0.0331^{***}	0.0015	–	(1) -0.0126^{**}	(1) -0.0137^{**}	0.2231
Cotton	−0.0583	1.7710^{***}	e+: −0.0031 e^{-}: −0.0030	0.1689	–	(3) -0.0123^{***}	–	0.2169

Notes: NARDL estimates on interdependencies between cryptocurrency and commodity returns are collected in this table. The **PCorr** statistic is defined by the null of PCorr = 0 as the Pearson correlation coefficient. **Coint** is a Wald test for cointegration defined as $\beta_1 = \beta_2 = \beta_3 = 0$. This equation (**Eq**) demonstrates long-term elasticities between cryptocurrency and commodity returns (Com): $R_{jt-i} = e^{+}\cdot Com^{+}_{t-I} + e^{-}\cdot Com^{-}_{t-i}$. **LAsym** is the Wald test for the long-term symmetry null defined as $-\beta_2/\beta_1 = -\beta_3/\beta_1$. In terms of short-run symmetry, **Says** is Wald's test for the null if $\gamma_i^{+} = \gamma_i^{-}$. The impact of the cumulative positive and negative variations in commodity returns for ()-lags on the top four cryptocurrency returns are shown by **Lags** $^{+}$ and **Lags** $^{-}$, respectively.

The statistical significance levels are 10%, 5%, and 1% for *, **, and ***, respectively. For small samples, critical values by Narayan (2005) are used.

All cryptocurrencies reject the no cointegration null hypothesis (column 3) for all commodities, with the exception of Cardano that just rejects the null hypothesis for platinum, natural gas and cotton. In addition, all changes in commodity returns show positive cointegration coefficients and they are greater than in the rest of the periods examined in this research. Therefore, this pandemic sub-period reveals long-term interconnections (cointegration) between changes in all commodities returns and all the cryptocurrencies returns, with several exceptions for Cardano. These results would be in line with some recent studies, such as Gonzalez et al. (2021), Jareño et al. (2021) and Kwapień et al. (2021), among others, regarding the increased interdependence of financial variables when economic conditions are turbulent, like the COVID-19 pandemic.

The cointegration equation results (column 4) evidence that the returns of all cryptocurrencies follow the same trend as returns on commodities whether they are positive or negative fluctuations. First, there is statistically significant long-run elasticities for the positive and negative cumulative variations in gold returns for Bitcoin and Ethereum, at the 1% significance level, and for Cardano, at the 5% significance level, with positive sign in the case of Bitcoin and negative sign in the case of Ethereum and Cardano. In the same vein, in the case of platinum, Bitcoin, Ethereum and Cardano cryptocurrencies have significant coefficients at 1%, with negative sign. On the other hand, the positive and negative cumulative variations in natural gas returns would show non-statistically significant long-run elasticities for any cryptocurrency. In the case of corn, Bitcoin and Tether cryptocurrencies coefficients are negative and statistically significant at the 10% and 1% level, respectively. Finally, in the case of cotton, negative and statistically significant long-run elasticities are observed for Ethereum and Cardano at 5% level. In addition, both elasticities exhibit similar coefficients for all cryptocurrencies and so, these cryptocurrencies respond the same to positive and to negative variations in commodities returns.

The Wald's long-term symmetry null hypothesis (column 5) would be rejected by Bitcoin and Ethereum at 10% significance level in the case of gold and, in the case of corn, the null hypothesis is also rejected by Bitcoin at a 10% significance level. In addition, these coefficients may show positive sign and statistically significance.

The Wald's short-term symmetry null hypothesis (column 6) may be rejected, in the case of gold, platinum and cotton, by Bitcoin, Ethereum and Cardano, with positive coefficients and statistically significant at a 1% level (except for the commodity gold in the case of Ethereum and Cardano, with a significance level of 5%). Based on these results, cryptocurrency returns asymmetrically respond in the short-term to fluctuations in these commodities returns. In the case of platinum, Tether rejects the null hypothesis at a 5% significance level with a negative coefficient. On the other hand, the results for natural gas reflect that Tether and Cardano reject the short-term symmetry null hypothesis with negative and positive coefficients respectively, being statistically significant at 10% in the case of Tether and 5% in the case of Cardano. Finally, in the case of corn, the null hypothesis is rejected by Bitcoin and Ethereum with positive coefficients and statistically significance at the 10% and 5% levels, respectively.

Regarding the impact of the total positive and negative variations in commodities returns for 1 to 4 lags (columns 7 and 8), there is no effect of the total amount of positive fluctuations in gold returns on any cryptocurrency in this COVID sub-period. In contrast, the cumulative negative variations in gold returns have a negative and statistically significant impact on Ethereum (at 5% significance level) and Cardano (at 10% level) returns, both for 1 lag. In the case of platinum returns, the impact of cumulative positive and negative fluctuations is negative and statistically significant on Tether returns for 2-lags and 1- and 3-lags, respectively. In another direction, the cumulative negative variations in platinum returns have a positive and statistically significant impact on Bitcoin, Ethereum and Cardano returns for 3-lags. The cumulative positive changes in natural gas returns would positively and statistically significantly influence Ethereum returns for 4-lags at 10% significance level. In contrast, the cumulative negative fluctuations in natural gas returns are negatively and statistically significant affecting Ethereum returns for 4 lags (at a 10% level) and Tether returns for 1 lag (at a 1% level). Regarding the commodity corn, statistically significant negative effects of the cumulative positive changes in corn returns are found on Cardano and Tether returns for 2- and 1-lags, respectively; in addition, statistically significant negative effects of the cumulative negative variations in corn returns are observed on Tether returns for 1 lag and at a 5% significance level. Finally, in the case of cotton, the cumulative positive changes in cotton returns are negatively and statistically significant affecting Tether returns for 3-lags at the 1% level of significance.

Overall, the explanatory power of our NARDL model, measured by the adjusted R^2 coefficient, improves substantially during the pandemic with respect to the entire period and the sub-period prior to COVID-19. Concretely, regarding gold, the adjusted R^2 coefficients vary from 5.30% for Cardano to 19.46% for Tether. Likewise, in the case of platinum, the adjusted R^2 coefficients vary from 13.35% for Cardano to 24.66% for Tether. In the case of natural gas, these coefficients vary from 3.67% for Ethereum to 22.39% for Tether. In the case of corn, they vary from 3.29% for Ethereum to 22.31% for Tether and, with respect to cotton, they vary from 6.37% for Bitcoin to 21.69% for Tether. Therefore, it is evident that there is a substantial increase in the explanatory power of the NARDL models when analysing the COVID sub-period, in accordance with the recent Gonzalez et al. (2021) research, among others. In addition, it is also noteworthy that the maximum adjusted R^2 values always correspond to Tether, which shows by far the highest explanatory power for all commodities during the COVID-19 pandemic.

5. Conclusions

The main objective of this paper is to explore the effect of the recent pandemic on the existing interdependencies between the returns of the cryptocurrencies Bitcoin, Ethereum, Cardano and Tether and the changes in the returns of the commodities gold, platinum, natural gas, corn and cotton, using the Nonlinear Autoregressive Distributed Lag model (NARDL). For greater robustness of our conclusions, three different sample periods are analysed. First, the full sample period spanning from March 1, 2018 to March 26, 2021 is analysed. During this sample period, two sub-periods were explored to test the robustness of the NARDL model and the skewness and cointegration checks. before and after the WHO officially declares the COVID-19 pandemic on March 11, 2020. The first one, sub-period prior to COVID-19, covers from March 1, 2018 to March 11, 2020, while the second one, called the COVID sub-period, spans from March 12, 2020 to March 26, 2021.

The results show that the NARDL model of the COVID sub-period exhibits the highest adjusted R^2, as well as that our regressions are more robust in this crisis period, in line with much of the financial literature, such as Naeem et al. (2020) and González et al. (2020a, 2020b), among many others. Interestingly, Tether shows the maximum values for the adjusted R^2 coefficients for all commodities during pandemic far away from the values of the other cryptocurrencies and periods. These results indicate that, in periods of economic crisis, Tether has a higher degree of interconnectedness with commodities than the other cryptocurrencies.

The main conclusions drawn from this study highlight that the Pearson correlation coefficient between commodity and cryptocurrency returns shows a greater robustness of statistically significant results in the pandemic, except for the commodity natural gas, in which there is no statistical significance in this sub-period and nevertheless, it is correlated with Tether before the COVID-19 and in the full period. As a general rule, gold, platinum, corn and cotton returns are positively and statistically significantly correlated with Bitcoin, Ethereum and Cardano returns, with the exception of Tether, during the pandemic. As regards gold returns, they are positively and statistically significantly correlated with Tether returns. We thus observe an evolution in the correlation of cryptocurrency and commodity returns that changes over time.

There is a long-term relationship (cointegration) between variations in commodity returns and all cryptocurrency returns (with a few isolated exceptions) during the pandemic. In contrast, prior to COVID-19, there is no cryptocurrency whose returns and changes in commodity returns have a long-run relationship (with the sole exception of two cryptocurrencies in the commodity natural gas) and, during the whole period, there is also cointegration in similar terms to the pandemic stage, except for Tether, which shows cointegration only with natural gas, whereas during the COVID-19 phase it showed cointegration with all commodities.

The cointegration expression indicates that cryptocurrency returns are impacted in the same way by positive or negative variations in commodity returns without exception. Tether, on the other hand, tends to have coefficients well below the other cryptocurrencies and the vast majority of the coefficients are negative in all sample periods studied. This shows that the movements in the returns of the Tether cryptocurrency occur in the opposite direction to those of commodities, which could be very useful for portfolio management, as it would allow diversifying the risk of portfolios, as well as even serving as a hedge against certain financial risks.

Common to all three sample periods studied is the non-existence of asymmetric effects in the long-term of commodities returns on most cryptocurrency returns. The only exceptions in the COVID sub-period in this respect appear in the results for the commodity gold and Bitcoin and Ethereum returns, as well as for the commodity corn and Bitcoin returns, where the long-term asymmetry could have statistically significance. Otherwise, the vast majority of cryptocurrencies may show statistically significant short-run asymmetry in the COVID-19 sub-period in all commodities analysed. However, before de pandemic, the general rule is the acceptance of the short-term symmetry null hypothesis (with few exceptions).

Finally, regarding the impact of the cumulative positive and negative fluctuations in commodity returns on the four leading cryptocurrencies returns, the persistence in the impact of negative variations in most commodities returns for all cryptocurrencies returns is higher in the COVID sub-period.

At last, as we have previously advanced, there are differences in the impact of changes in commodities returns on the four leading cryptocurrencies returns. The explanatory power of the NARDL models is different in each period analysed and with notable differences, as the strength is much higher during the pandemic, in line with previous work such as Gonzalez et al. (2021), among others. Furthermore, the highest adjusted R^2 values always correspond to Tether, which shows by far the highest explanatory power for all commodities during the COVID-19. This may lead us to think of its possible role as a hedge, safe haven, or diversifier.

From the above, we can state that the results of the regressions according to the NARDL methodology would be consistent with recent studies analysed in this research which state that the interdependence between this type of financial variables depends on the economic situation, and therefore there is a large effect of the COVID-19 pandemic crisis, explored in depth in this study. Moreover, this paper corroborates that the connection between commodity and cryptocurrency markets, in terms of cointegration, short- and long-term asymmetry, and lag persistence, among others, are mostly centered on the pandemic outbreak. In line with González et al. (2021), the most relevant hypothesis about the fact that the connection between commodity and cryptocurrency returns is intensified in crisis periods, such as the COVID-19 pandemic, is confirmed due to the higher adjusted R^2 values of the NARDL model mainly during the COVID sub-period.

Consistently, the results obtained are in line with previous literature, as we observe a higher level of connectedness in the different financial markets (cryptocurrencies and commodities) during turbulent stages, such as the COVID-19 pandemic period. In periods of uncertainty, when certain commodities such as corn, cotton or even platinum could become scarce, financial markets are much more interconnected and suffer largely from the contagion effect. Therefore, the use of some cryptocurrencies as a safe haven asset, hedge or diversification could play a key role in possible investment strategies. The impact that these effects would have on different economic sectors would need a much more detailed analysis that could be developed in future research. In addition, regarding how the results have changed in the middle of the COVID-19 period, some recent research is exploring the idea that this is likely due to the emergence of the COVID-19 vaccine. Therefore, a future line of research already open is focused on shedding light on this issue. Some lines of further study may consist of a progressive update of the analysis to know the effect of the successive waves of contagions and their impact on the global economic situation, since this influences commodity and also of cryptocurrency returns, thus being able to study the interdependencies between the two. Likewise, an interesting research is the scenario we expect to encounter in the coming months, with the analysis of the effect of vaccines on the number of contagions, thus analysing the effect of the progressive economic recovery on the interdependence of these variables.

The cryptocurrency market has reached, in the sample period studied, historical highs and also historical lows, which has been of special interest for this study. Thus, this research has had the opportunity to explore a currently volatile market, which undoubtedly has an impact on our results as well. Therefore, another potential research could be to analyse the impact of the cryptocurrency market on the rest of the financial markets, taking into account that every day this cryptocurrency is accepted as a means of exchange by national governments and that more and more companies are accepting them as a means of payment, despite the recent comments of Elon Musk (Tesla Motors). We will keep an eye on the evolution of the market.

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Conflict of interest

The authors declare no conflict of interest.

References

Adekoya OB, Oliyide JA, Oduyemi GO (2021) How COVID-19 upturns the hedging potentials of gold against oil and stock markets risks: Nonlinear evidences through threshold regression and markov-regime switching models. *Resour Policy* 70: 101926. https://doi.org/10.1016/j.resourpol.2020.101926

Algieri B (2017) Assessing contagion risk from energy and non-energy commodity markets. *Energy Econ* 62: 312–322. https://doi.org/10.1016/j.eneco.2017.01.006

Ante L (2020) Bitcoin transactions, information asymmetry and trading volume. *Quant Financ Econ* 4: 365–381. https://doi.org/ 10.3934/QFE.2020017

Arize AC, Malindretos J, Igwe EU (2017) Do exchange rate changes improve the trade balance: An asymmetric nonlinear cointegration approach. *Int Rev Econ Financ* 49: 313–326. https://doi.org/10.1016/j.iref.2017.02.007

Balli F, Farid S, Shahzad SJH, et al. (2019) Spillover network of commodity uncertainties. *Energy Econ* 81: 914–927. https://doi.org/10.1016/j.eneco.2019.06.001

Bongards O, Czudaj RL, Van Hoang TH (2021) Price overreactions in the commodity futures market: An intraday analysis of the Covid-19 pandemic impact. *Resour Policy* 71: 101966. https://doi.org/10.1016/j.resourpol.2020.101966

Bouri E, Gupta R, Lahiani A, et al. (2018) Testing for asymmetric nonlinear short- and long-run relationships between bitcoin, aggregate commodity and gold prices. *Resour Policy* 57: 224–235. https://doi.org/10.1016/j.resourpol.2018.03.008

Bouri E, Jalkh N, Molnár P, et al. (2017). Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven? *Appl Econ* 50: 5063–5070. https://doi.org/10.1080/00036846.2017.1299102

Brock WA, Dechert WD, Scheinkman JA, et al. (1996) A Test for Independence Based on the Correlation Dimension. *Econometric Rev* 15: 197–235. https://doi.org/10.1080/07474939608800353

Canh NP, Binh NQ, Thanh SD (2019) Cryptocurrencies and Investment Diversification: Empirical Evidence from Seven Largest Cryptocurrencies. *Theor Econ Lett* 9: 431–452. https://doi.org/10.4236/tel.2019.93031

Charfeddine L, Benlagha N, Maouchi Y (2020) Investigating the dynamic relationship between cryptocurrencies and conventional assets: Implications for financial investors. *Econ Model* 85: 198–217. https://doi.org/10.1016/j.econmod.2019.05.016

Ciaian P, Rajcaniova M, d'Artis K (2018) Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets. *J Int Financ Mark Inst Money* 52: 173–195. https://doi.org/10.1016/j.intfin.2017.11.001

Conlon T, McGee R (2020) Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. *Financ Res Lett* 35: 101607. https://doi.org/10.1016/j.frl.2020.101607

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

Corbet S, Hou YG, Larkin C, et al. (2020b) Any port in a storm: Cryptocurrency safe-havens during the COVID-19 pandemic. *Econ Lett* 194: 109337. https://doi.org/10.1016/j.econlet.2020.109377

Corbet S, Meegan A, Larkin C, et al. (2018) Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Econ Lett* 165: 28–34. https://doi.org/10.1016/j.econlet.2018.01.004

Demir E, Simonyan S, García-Gómez CD, et al. (2021) The asymmetric effect of bitcoin on altcoins: evidence from the nonlinear autoregressive distributed lag (NARDL) model. *Financ Res Lett* 40: 101754. https://doi.org/10.1016/j.frl.2020.101754

Demiralay S, Golitsis P (2021) On the dynamic equicorrelations in cryptocurrency market. *Q Rev Econ Financ* 80: 524–533. https://doi.org/10.1016/j.qref.2021.04.002

Ferrer R, Jawad S, López R, et al. (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

González M, Jareño F, Skinner FS (2020a) Nonlinear Autoregressive Distributed Lag Approach: An Application on the Connectedness between Bitcoin Returns and the Other Ten Most Relevant Cryptocurrency Returns. *Mathematics* 8: 810. https://doi.org/10.3390/math8050810

González M, Jareño F, Skinner F (2020b) Portfolio Effects of Cryptocurrencies During the COVID-19 Crisis, En C. Bagnoli, M. Billio , & S. Varotto (Edits.), *A New World Post COVID-19, Lessons for Business,the Finance Industry and Policy Makers*, Venezia: Edizioni Ca' Foscari—Digital Publishing, 149–161. http://doi.org/10.30687/978-88-6969-442-4

González MO, Jareño F, Skinner FS (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 JW, Goutte S (2021) Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis. *Financ Res Lett* 38: 101625. https://doi.org/10.1016/j.frl.2020.101625

Gyamerah SA (2019) Modelling the volatility of Bitcoin returns using GARCH models. *Quant Financ Econ* 3: 739–753. https://doi.org/10.3934/QFE.2019.4.739

Jareño F, González MO, López R, et al. (2021) Cryptocurrencies and oil price shocks: A NARDL analysis in the COVID-19 pandemic. *Resour Policy* 74: 102281. https://doi.org/10.1016/j.resourpol.2021.102281

Jareño F, Tolentino M, González MO, et al. (2019) Impact of changes in the level, slope and curvature of interest rates on US sector returns: an asymmetric nonlinear cointegration approach. *Econ Res* 32: 1275–1297. https://doi.org/10.1080/1331677X.2019.1632726

Jareño F, González M, Tolentino M, et al. (2020) Bitcoin and Gold Price Returns: A Quantile Regression and NARDL Analysis. *Resour Policy* 67: 101666. https://doi.org/10.1016/j.resourpol.2020.101666

Ji Q, Bouri E, Roubaud D, et al. (2018) Risk spillover between energy and agricultural commodity markets: A dependence-switching CoVaR-copula model. *Energy Econ* 75: 14–27. https://doi.org/10.1016/j.eneco.2018.08.015

Ji Q, Zhang D, Zhao Y (2020) Searching for safe-haven assets during the COVID-19 pandemic. *Int Rev Financ Anal* 71: 101526. https://doi.org/10.1016/j.irfa.2020.101526

Jiang Y, Lie J, Wang J, et al. (2021) Revisiting the roles of cryptocurrencies in stock markets: A quantile coherency perspective. *Econ Model* 95: 21–34. https://doi.org/10.1016/j.econmod.2020.12.002

Kang SH, McIver R, Yoon SM (2017) Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Econ* 62: 19–32. https://doi.org/10.1016/j.eneco.2016.12.011

Koirala KH, Mishra AK, D'Antoni JM, et al. (2015) Energy prices and agricultural commodity prices: Testing correlation using copulas method. *Energy* 81: 420–436. https://doi.org/10.1016/j.energy.2014.12.055

Kwapień J, Wątorek M, Drożdż S (2021) Cryptocurrency Market Consolidation in 2020–2021. *Entropy* 23: 1674. https://doi.org/10.3390/e23121674

Lin B, Su T (2021) Does COVID-19 open a Pandora's box of changing the connectedness in energy commodities? *Res Int Bus Financ* 56: 101360. https://doi.org/10.1016/j.ribaf.2020.101360

Mariana CD, Ekaputra IA, Ananto ZH (2021) Are Bitcoin and Ethereum safe-havens for stocks during the COVID-19 pandemic? *Financ Res Lett* 38: 101798. https://doi.org/10.1016/j.frl.2020.101798

Naeem MA, Farid S, Balli F, et al. (2020) Hedging the downside risk of commodities through cryptocurrencies. *Appl Econ Lett* 28: 153–160. https://doi.org/10.1080/13504851.2020.1739609

Nazlioglu S (2011) World oil and agricultural commodity prices: Evidence from nonlinear causality. *Energy Policy* 39: 2935–2943. https://doi.org/10.1016/j.enpol. 2011.03.001

Pabuçcu H, Ongan S, Ongan A (2020) Forecasting the movements of Bitcoin prices: an aplication of machine learning algorithms. *Quant Financ Econ* 4: 679–692. https://doi.org/10.3934/QFE.2020031

Papadamou S, Kyriazis NA, Tzeremes PG (2021a) Non-linear causal linkages of EPU and gold with major cryptocurrencies during bull and bear markets. *North Am J Econ Financ* 56: 101343. https://doi.org/10.1016/j.najef.2020.101343

Papadamou S, Kyriazis NA, Tzeremes PG, et al. (2021b) Herding behaviour and price convergence clubs in cryptocurrencies during bull and bear markets. *J Behav Exp Financ* 30: 100469. https://doi.org/10.1016/j.jbef.2021.100469

Pesaran M, Shin Y (1999) An autoregressive distributed lag modelling approach to cointegration analysis, In: Storm, S. (Ed.), *Econometrics and Economic Theory in the 20th Century: the Ragnar Frisch Centennial Symposium*, Cambridge University Press, Cambridge.

Peterson OJ, Anokye MA, Tweneboah G, et al. (2020) Connectedness of cryptocurrencies and gold returns: Evidence from frequency-dependent quantile regressions. *Cogent Econ Financ* 8: 1. https://doi.org/10.1080/23322039.2020.1804037

Rajput H, Changotra R, Rajput P, et al. (2020) A shock like no other: coronavirus rattles commodity markets. *Environ Dev Sustainability* 11: 1–12. https://doi.org/10.1007/s10668-020-00934-4

Salisu AA, Akanni L, Raheem I (2020) The COVID-19 global fear index and the predictability of commodity price returns. *J Behav Exp Finance* 27: 100383. https://doi.org/10.1016/j.jbef.2020.100383

Shin Y, Yu B, Greenwood-Nimmo M (2014) Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework, In: *Festschrift in Honor of Peter Schmidt*, Springer Science and Business Media LLC: New York, NY, 281–314.

Shruthi MS, Ramani D (2021) Statistical analysis of impact of COVID 19 on India commodity markets. *Mater Today Proc* 37: 2306–2311. https://doi.org/10.1016/j.matpr.2020.07.729

Sifat I (2021) On cryptocurrencies as an independent asset class: Long-horizon and COVID-19 pandemic era decoupling from global sentiments. *Financ Res Lett,* 102013. https://doi.org/10.1016/j.frl.2021.102013

Smales LA (2019) Bitcoin as a safe haven: is it even worth considering? *Financ Res Lett* 30: 385–393. https://doi.org/10.1016/j.frl.2018.11.002

Symitsi E, Chalvatzis KJ (2019) The economic value of Bitcoin: A portfolio analysis of currencies Gold oil and stocks. *Res Int Bus Financ* 48: 97–110. https://doi.org/10.1016/j.ribaf.2018.12.001

Umar Z, Gubareva M (2020) A time–frequency analysis of the impact of the Covid-19 induced panic on the volatility of currency and cryptocurrency markets. *J Behav Exp Financ* 28: 100404. https://doi.org/10.1016/j.jbef.2020.100404

Umar Z, Jareño F, Escribano A (2021a) Agricultural commodity markets and oil prices: An analysis of the dynamic return and volatility connectedness. *Resour Policy* 73: 102147. https://doi.org/10.1016/j.resourpol.2021.102147

Umar Z, Jareño F, Escribano 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 Social Change* 172: 121025, https://doi.org/10.1016/j.techfore.2021.121025

Wang G, Tang Y, Xie C, et al. (2019) Is bitcoin a safe haven or a hedging asset? Evidence from China. *J Manage Sci Eng* 4: 173–188. https://doi.org/10.1016/j.jmse.2019.09.001

Wu S, Tong M, Yang Z, et al. (2019) Does gold or Bitcoin hedge economic policy uncertainty? *Financ Res Lett* 31: 171–178. https://doi.org/10.1016/j.frl.2019.04.001

Xiao H (2020) Forecasting the Returns of Cryptocurrency: A Model Averaging Approach. *J Risk Financ Manage* 13: 278. https://doi.org/10.3390/jrfm13110278

Zivot E, Andrews DWK (1992) Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis. *J Bus Econ Stat* 10: 251–270. https://doi.org/10.1198/073500102753410372