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Nonlinear Autoregressive Distributed Lag Approach: An Application on the Connectedness between Bitcoin Returns and the Other Ten Most Relevant Cryptocurrency Returns

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Abstract: This article examines the connectedness between Bitcoin returns and returns of ten additional cryptocurrencies for several frequencies—daily, weekly, and monthly—over the period January 2015–March 2020 using a nonlinear autoregressive distributed lag (NARDL) approach. We find important and positive interdependencies among cryptocurrencies and significant long-run relationships among most of them. In addition, non-Bitcoin cryptocurrency returns seem to react in the same way to positive and negative changes in Bitcoin returns, obtaining strong evidence of asymmetry in the short run. Finally, our results show high persistence in the impact of both positive and negative changes in Bitcoin returns on most of the other cryptocurrency returns. Thus, our model explains about 50% of the other cryptocurrency returns with changes in Bitcoin returns.

Keywords: Bitcoin; cryptocurrencies; NARDL; connectedness

1. Introduction

The importance of the cryptocurrency market has continued to increase, even in recent years. References [1,2] highlighted that the cryptocurrency market was worth more than $12.5 billion in 2016. Additionally, reference [2] noticed the growing popularity of the cryptocurrency markets, now being suggested in the literature as an investment asset, and highlighting that the price of the most liquid cryptocurrency—Bitcoin price—increased about 700%, from $616 to $4800 US dollars between October 2016 and October 2017. Presently, the overall cryptocurrency market is even more important as the total cryptocurrency market capitalization is $251.5 billion on 7 March 2020 and the Bitcoin price has increased almost 3300% from $269.2 to $8887.8 US dollars between the beginning (26 January 2015) and the final (7 March 2020) date of the sample period.

Furthermore, Bitcoin dominance in the cryptocurrency market is increasing. Reference [3] confirmed that Bitcoin's capitalization was about 37% of the cryptocurrency market on 1 May 2018 but now, merely two years later, Bitcoin's market share is about 66% on 7 March 2020. Therefore, Bitcoin is the most globally recognized cryptocurrency in terms of capitalization and the number of users. Additionally, reference [4] notes that the cryptocurrencies' market reached a peak in early 2018 with the market's capitalizations of $800 billion and suggests that cryptocurrencies can now be considered to be an alternative investment option for everyone. This spectacular growth attracted the attention of regulation authorities, big corporations, and small investors.

In this context, a wide and recent branch of the financial literature has focused on studying the cryptocurrency market. Thus, many kinds of research analyze potential connectedness between different altcoins in the cryptocurrency market, as well as between cryptocurrencies and alternative financial assets. These studies apply different methodologies such as: Autoregressive Distributed Lag (ARDL) model in [1]; several Diebold and Yilmaz type approach [5–7] in [8,9]; Vector AutoRegressive (VAR) and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) methodologies in [3,10–12]; BEKK-GARCH framework in [13–16]; and other innovative approaches in [4,17], among many others. All of them find important interdependencies between many altcoins of the cryptocurrency market.

Thus, the main aim of this research is to explore potential long- and short-run connectedness between Bitcoin returns and the rest of the recent (March 2020) top 10 cryptocurrency returns (Ethereum, XRP, Bitcoin Cash, Tether, Bitcoin SV, Litecoin, EOS, Binance coin and Tezos). For robustness, these estimates are repeated for different frequencies (daily, weekly, and monthly) for a sample period from 26 January 2015 to 7 March 2020 in a nonlinear ARDL framework.

This paper contributes to the previous literature in several ways. First, to the best of our knowledge, this is the first research that simultaneously estimates both long- and short-run asymmetries in the cryptocurrency markets. This is accomplished by using the NARDL approach [2,18] to examine the relationship between Bitcoin returns and the remaining top 10 cryptocurrencies' returns. References [2,18,19] affirm that some of the main advantages of the NARDL methodology is that it is suitable for small samples regardless of the stationarity of the variables. Additionally, this methodology checks simultaneously long- and short-run nonlinearities by estimating positive and negative partial sum decompositions of the regressors. Also, the NARDL approach separately measures responses to positive and negative shocks of the regressors from the asymmetric dynamic multipliers. Second, this research studies in depth the potential connectedness between Bitcoin and the nine alternative named cryptocurrencies. Alternative cryptocurrencies have been selected as the largest market capitalizations as reported on 7 March 2020 from the Coinmarketcap site. Finally, for robustness, this study compares estimates for daily, weekly, and monthly frequencies.

The rest of the paper is structured as follows. Section 2 develops a wide literature review concerning the interdependence among different altcoins of the cryptocurrency market. Section 3 presents the data and the methodology applied in this study. Section 4 collects the main results of our NARDL estimates, distinguishing three different sub-sections depending on the frequency (daily, weekly, and monthly) of the data. Finally, Section 5 summarizes and presents concluding remarks and comments on potential implications and future research.

2. Literature Review

The number of empirical studies analyzing cryptocurrencies has grown exponentially in the recent years in the financial literature. Thus, reference [20] performs a rigorous review of financial literature about the cryptocurrency market, remarking that cryptocurrencies must face charges of potential illicit use and inexperienced exchange systems, among others. Some additional recent examples of research include reference [2] that studies the relationship between Bitcoin and Gold price returns, finding a positive and statistically significant connectedness, and reference [21] that remark the prevalence of cryptocurrencies with over 2000 Bitcoin-like cryptocurrencies now in use among many recent contributions.

However, a recent important extension of the literature examines the relationships among Bitcoin and other alternative cryptocurrencies. Reference [1] proposes the autoregressive distributed lag (ARDL) methodology to study interdependencies between the reference cryptocurrency Bitcoin plus other alternative virtual currencies and two altcoin markets in the short and long run for the period 2013–2016. They find that there is a statistically significant relationship between Bitcoin and altcoin markets, mainly in the short run. Using the same ARDL approach, reference [22] checks if the new coin events significantly influence Bitcoin returns. They find evidence that Initial Public Offerings (IPOs) of new altcoins reduce Bitcoin returns.

Reference [23] studies potential co-movements between Bitcoin and some relevant cryptocurrencies (Dash, Ethereum, Litecoin, Monero and Ripple) using wavelet techniques. The find co-movements in the following relationships: Bitcoin-Dash, Bitcoin-Monero, Bitcoin-Ripple and additionally they find evidence of important diversification abilities with an Ethereum-Bitcoin portfolio in the long-term, and Monero-Bitcoin portfolio in the short-term. Reference [24] uses wavelet-based methods to analyze the time-varying co-movement patterns of some relevant cryptocurrency prices (Bitcoin, Ethereum, Lite, and Dashcoin). First, using wavelet multiple correlation and cross-correlation, they show Bitcoin could be the potential market leader. Additionally, they estimate wavelet local multiple correlation for the aforementioned cryptocurrency prices across different time-scales concluding that the correlation follows an aperiodic cyclical pattern and that the cryptocurrency prices are driven by Bitcoin price fluctuations, with important implications for investment purposes. Reference [25] applies the cross-quantilogram approach to study the hedging abilities of some relevant cryptocurrencies against down fluctuations in the US stock market and US sector indices. They find very heterogeneous results that help investors to manage cryptocurrencies portfolios. Reference [26] analyzes the volatility movements of the most important cryptocurrencies (Bitcoin and Ether) by using a bivariate Diagonal BEKK model. This research finds evidence of interdependencies in the cryptocurrency market as well as the effects of important events on volatility with important implications for informed decision-making by investors.

In the same vein, reference [8] measures interdependencies between the most important cryptocurrencies' returns and volatilities, using the Diebold and Yilmaz approach [5]. They suggest an emergent and time-varying interdependence between the cryptocurrencies analyzed. One of the recent methodologies is applied in [9], specifically the Diebold and Yilmaz measures [6,7], to study potential return and volatility connectedness among six cryptocurrencies. They discover that changes in Litecoin and Bitcoin returns show the most relevant impact on the rest of cryptocurrencies. Furthermore, Bitcoin and Litecoin show the highest and Dash the lowest volatility connectedness, confirming the hedging potential of Bitcoin and Litecoin when constructing portfolios with cryptocurrencies. Reference [27] estimates market-herding dynamics in the cryptocurrency market by adapting the Capital Asset Pricing Model (CAPM) framework as developed earlier by [28]. Thus, this methodology explores time variation in betas and cross-sectional dispersion of individual assets, showing a recent growing market herding.

Some other research, such as [3], uses a VAR modelling methodology to study the information transmission between the most important cryptocurrencies (Bitcoin, Litecoin, Ripple, Ethereum, and Bitcoin Cash). Specifically, by obtaining the Geweke's feedback measures and generalized impulse response functions, they confirm a strong contemporaneous information transmission, and some lagged feedback effects, mainly from other cryptocurrencies to Bitcoin. Reference [10] examines potential spillovers between Bitcoin and companies in the energy and technology sector in the context of an asymmetric multivariate VAR-GARCH methodology. They find statistically significant return and short-run volatility spillovers from (mainly technology) companies to Bitcoin and long-run volatility spillovers from Bitcoin to energy companies. Reference [11] uses several time-varying copula methods and bivariate dynamic conditional correlation GARCH models to examine the financial properties of cryptocurrencies and their dynamic relationship with some financial and commodity assets. They discover some important implications for investors, as the cross-correlation with conventional assets is changeable over time, depending on economic shocks. Additionally, cryptocurrencies may be suitable for financial diversification, but may form poor hedging instruments. Reference [12] applying the GARCH-MIDAS approach to forecast volatility of some relevant cryptocurrencies using different data frequencies. In addition, they propose different economic and financial drivers. They conclude that Global Real Economic Activity provides better volatility forecasts in bull and bear markets.

Reference [13] uses a multivariate BEKK-GARCH methodology and impulse response analysis applied within a VAR model to check potential hedging properties and volatility spillovers between Bitcoin and Ethereum. They find that the connectedness between them is time-variant and decreases the

potential diversification properties over time. These results have implications for investment strategies mainly during economic turmoil. Reference [14] applies pairwise bivariate BEKK models to study interlinkages and conditional correlations between different pairs of cryptocurrencies. Specifically, they analyze Bitcoin-Ether, Bitcoin-Litecoin, and Ether-Litecoin, pairs finding evidence of bi-directional effects in Bitcoin-Ether and Bitcoin-Litecoin, and uni-directional spillover from Ether to Litecoin. Furthermore, bi-directional volatility spillovers are found in all cases, as well as time-varying and positive conditional correlations. Reference [15] applies Diagonal BEKK and Asymmetric Diagonal BEKK methodologies on eight cryptocurrencies (Bitcoin, Ethereum, Litecoin, Dash, Ethereum Classic, Monero, Neo and OmiseGO) to study conditional volatility dynamics among them and their volatility co-movements. They find that cryptocurrencies have high term persistence of volatility, show strong interdependencies between them and have time-varying and positive conditional correlations. In the same vein, reference [16] uses the Granger causality test and a BEKK-MGARCH approach to study the return and volatility spillovers between Bitcoin and Litecoin. They show that both return and volatility spillovers run in one direction, from Bitcoin to Litecoin.

Reference [29] studies, among other topics, the weak-form market efficiency in the cryptocurrency market analyzing the measure "price delay" showing that it significantly decreases over time thereby supporting weak-form efficiency of the cryptocurrency market. Reference [30] studies Bitcoin, Litecoin, Ripple and Dash portfolio optimization and the correlation between them showing that the Black–Litterman model with Variance-Based Constraints (VBCs) offers better out-of-sample estimates than other benchmarks. Therefore, investors should apply more advanced approaches such as the Black–Litterman model to better manage cryptocurrency portfolios. Reference [31] studies many (smaller and larger) cryptocurrencies and the potential existence of herding in this market, showing inefficiency and excessive risk only in economic turmoil. In addition, smaller cryptocurrencies may be herding with larger ones. Reference [32] studies the relationship between returns and volatility of Bitcoin, at both contemporaneous and intertemporal levels, employing high-frequency data. Thus, there could be a negative, statistically significant, and contemporaneous link between all volatility measures and Bitcoin returns, but weak evidence in case of realized variance, jump variation, and downside realized semivariance. Additionally, there is no justification for a positive risk-return trade-off in Bitcoin markets. Reference [33] remarks on the relevance of correlation networks on the evolution of cryptocurrency prices over time and finds a positive and statistically significant connectedness between different cryptocurrencies. Specifically, one group of cryptocurrencies could be particularly correlated with Cardano while another group associated with Ethereum.

Some of the literature use novel approaches. Reference [4] applies descriptive metrics from Complex Networks to study the price synchronization in the cryptocurrency market. Specifically, they employ the Threshold Weighted—Minimum Dominating Set (TW-MDS) methodology to detect dominant cryptocurrencies over time, assuming that a dominant node would describe the behavior of the cryptocurrency market. They conclude that there is strong evidence of a growing price synchronization in this market. Reference [34] applies the generalized variance decomposition methodology, which enables the construction of a directional weighted network to study the connectedness between return and volatility of many cryptocurrencies. She finds highly connected cryptocurrencies mainly during shocks and some cryptocurrencies (Ethereum, Monero, OmiseGo) have more impact on the market than others. Additionally, some cryptocurrencies are less connected and less affected by shocks implying they are more attractive for investment purposes. Reference [17] analyzes the structure of the cryptocurrency market and propose the Bitcoin-Ethereum filtering mechanism (based on the agglomerative hierarchical clustering and minimum spanning tree) to exclude their linear influences with other cryptocurrencies. For robustness, they examine the market structures before and after filtering in terms of the Total, Pre-, and Post-regulation periods. They find evidence that Bitcoin and Ethereum are leaders in the cryptocurrency market, there are six other clusters of cryptocurrencies, and market structures renovate after the announcement of new regulations from several countries.

Reference [35] uses cointegrating tests and Vector Error Correction (VEC) Granger Causality/Block Exogeneity Test approaches to research the Bitcoin–Altcoin price synchronization hypothesis for ten altcoins, specifically Litecoin, Dash, Doge, IOTA, Nem, Neo, Stellar, Ripple and Tron for three different sub-periods: 2015–2016, 2017, and 2018. They find cryptocurrency investors are more sensitive to the features and quality of each coin during 2018 than for 2017. Reference [36] provides a systematic survey of return and volatility spillovers of cryptocurrencies, considering other cryptocurrencies and alternative assets. Thus, Bitcoin is the most relevant cryptocurrency mainly as a transmitter, but also as a receiver of spillovers. Furthermore, Bitcoin shows the most important connectedness with Ethereum, Litecoin, and Ripple. Return spillovers are more pronounced than volatility bi-directional spillovers. Finally, reference [36] detects volatility transmission among Bitcoin and national currencies. Reference [37] applies multivariate extreme value theory and they estimate a bias-corrected extreme correlation coefficient to study the contemporaneous tail dependence structure in pairwise comparisons of a large number of cryptocurrencies (Bitcoin, Dash, Dogecoin, Ethereum, Litecoin, Monero, Namecoin, Novacoin, Peercoin, and Ripple). They find significantly high bivariate dependency in the distribution tails of some of the most important cryptocurrencies. Thus, extreme correlations increase in bear markets, but not in bull markets for the pairs studied. Moreover, many cryptocurrency pairs show a low level of dependency in the tails of the distribution. Reference [38] uses panel ordinary least squares with cluster-robust standard errors to research the field of Tokenomics studying many blockchain tokens. This paper analyzes the potential connectedness between non-digital entities and digital tokens, finding that token functions significantly affect token prices regardless of the stage of the business cycle. Finally, reference [39] studies the diversification capability of some cryptocurrencies (Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash, and Bytecoin) against certain economic risks such as changes in oil price, gold price, interest rate, USD strength, and the stock market. Thus, they show structural breaks and Autoregressive Conditional Heteroskedastic (ARCH) disturbance in each cryptocurrency, suggesting a systematic risk within the cryptocurrency market. Furthermore, cryptocurrencies could have insignificant correlations with economic risk factors, reducing their diversification abilities.

Thus, to the best of our knowledge, this paper contributes to this previous literature in several ways. First, this research studies in depth the potential connectedness between Bitcoin and many other important cryptocurrencies in terms of recent market capitalization using the NARDL approach. The advantage of this methodology is that it enables us to simultaneously estimate both long- and short-run asymmetries [2,18]. Additionally, for robustness, this study compares estimates from several frequency data (daily, weekly, and monthly).

3. Materials and Methods

3.1. Data

Our data set consists of daily, weekly, and monthly log returns of the top ten cryptocurrencies ranked by market capitalization. These ten cryptocurrencies ordered from highest to lowest by market capitalization are Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Bitcoin_cash (BCH), Tether (USDT), Bitcoin_sv (BSV), Litecoin (LTC), EOS, Binance_coin (BNB) and Tezos (XTZ). The data is provided by the Coinmarketcap website. These top ten cryptocurrencies under study represent, on average, over 92% of the cryptocurrency market capitalization and Bitcoin shows approximately 66% dominance in this market, on 7 March 2020.

Our sample period runs from 26 January 2015 until 7 March 2020, which yields 1868 daily, 267 weekly, and 61 monthly data observations. The starting point is imposed by the price availability of some cryptocurrencies and the end of this period is established just before the massive selloff in the cryptocurrency market on 8 March 2020 and the recent stock market crash on 9 March 2020 caused by COVID-19. Due to this massive selloff, the cryptocurrency market lost $21 billion in market capitalization in 24 hours from Saturday 7 March 2020 to Sunday 8 March 2020 (from a total cryptocurrency market capitalization of $251.5 billion to $230.8 billion). Moreover, two weeks later,

on 22 March 2020, the cryptocurrency market has lost more than $84 billion because of COVID-19, falling to a total of $167.1 billion. It is remarkable that despite the big drop in cryptocurrency market capitalization, Bitcoin still has a 65.1% dominance of this market on 22 March 2020. These top ten cryptocurrencies did not come into existence at the same time. The starting date for each cryptocurrency is shown in column 7 of Table 1. Therefore, the most recent cryptocurrencies, especially Bitcoin_sv and Tezos, will provide fewer monthly data for the empirical analysis.

Table 1. Top 10 Cryptocurrencies by Market Capitalization (Date: 7 March 2020/22 March 2020) (Total market capitalization: $251.5 billion/$167.1 billion). [1]

Name	Market Cap	Price	Volume (24 h)	Circulating Supply	Change (24 h)	Starting Date
Bitcoin	$166,743,993,933	$8887.80	$47,868,579,352	18,238,800 BTC	−0.21%	01/26/2015
	$106,591,196,069	$5830.25	$40,099,664,740	18,282,425 BTC	−5.73%	
Ethereum	$26,966,016,878	$237.32	$25,206,666,119	109,863,231 ETH	2.07%	03/10/2016
	$13,590,860,527	$123.32	$12,497,707,224	110,207,055 ETH	−7.05%	
XRP	$10,688,702,708	$0.23624	$3,252,412,868	43,749,413,421 XRP	−0.88%	01/26/2015
	$6,585,765,149	$0.150214	$1,864,979,798	43,842,625,397 XRP	−5.02%	
Bitcoin_Cash	$6,364,459,307	$330.77	$6,617,099,625	18,300,000 BCH	−0.25%	08/03/2017
	$3,736,418,941 (5)	$203.67	$4,015,953,536	18,345,250 BCH	−7.47%	
Tether	$4,641,437,047	$1.0047	$66,519,050,406	4,642,367,414 USDT	0.16%	04/15/2017
	$4,637,871,717 (4)	$0.99903	$49,036,623,749	4,642,367,414 USDT	−0.21%	
Bitcoin_SV	$4,439,960,724	$233.95	$3,344,789,290	18,297,290 BSV	−1.66%	11/19/2018
	$2,894,145,363	$157.78	$3,365,019,330	18,342,440 BSV	−6.35%	
Litecoin	$4,072,866,599	$60.45	$6,342,837,357	64,168,987 LTC	−0.77%	08/24/2016
	$2,292,391,578	$35.63	$3,148,219,029	64,342,318 LTC	−7.34%	
EOS	$3,526,893,934	$3.64	$6,064,573,978	920,452,308 EOS	−0.47%	07/02/2017
	$1,965,191,547	$2.13	$2,921,411,201	921,045,767 EOS	−6.45%	
Binance Coin	$3.292,877,236	$20.24	$427,799,971	155,536,713 BNB	−1.68%	11/09/2017
	$1,735,514,181	$11.16	$308,670,064	155,536,713 BNB	−7.48%	
Tezos	$2,250,710,445	$2.98	$317,321,520	702,028,555 XTZ	−0.04%	02/02/2018
	$1,038,511,561	$1.47	$113,589,399	704,565,511 XTZ	−11.11%	

[1] Compiled by the authors, based on the information provided by the *Coinmarketcap* website.

Figure 1 plots the time evolution of the cryptocurrencies' daily prices up to the end of March 2020 and so incorporates the COVID-19 crash of 8 March 2020. Consequently, the market capitalization of the top ten cryptocurrencies analyzed in this paper has decreased sharply on March 8, ranging from 53.8% for Tezos to 38.3% for Ripple while Bitcoin suffered a lower loss 36% (though not as low as 34.7% for Bitcoin_sv). Interestingly, Tether is an outlier by experiencing a very modest one day loss of 0.065%. Table 1 also shows that two weeks after the COVID-19 crash, the total cryptocurrency market capitalization has fallen by almost 40% from $251.5 billion to $167.1 billion and these top ten cryptocurrencies have decreased in value between 32% and 50%, except in the case of Tether, where this decrease is only 0.5%.
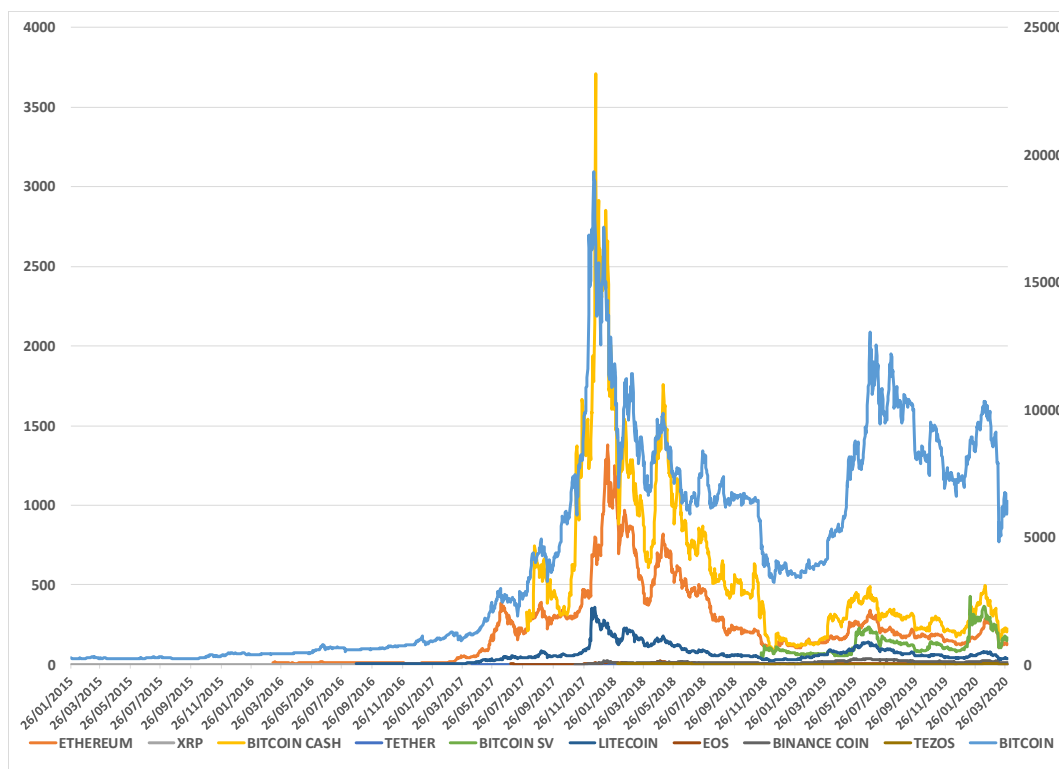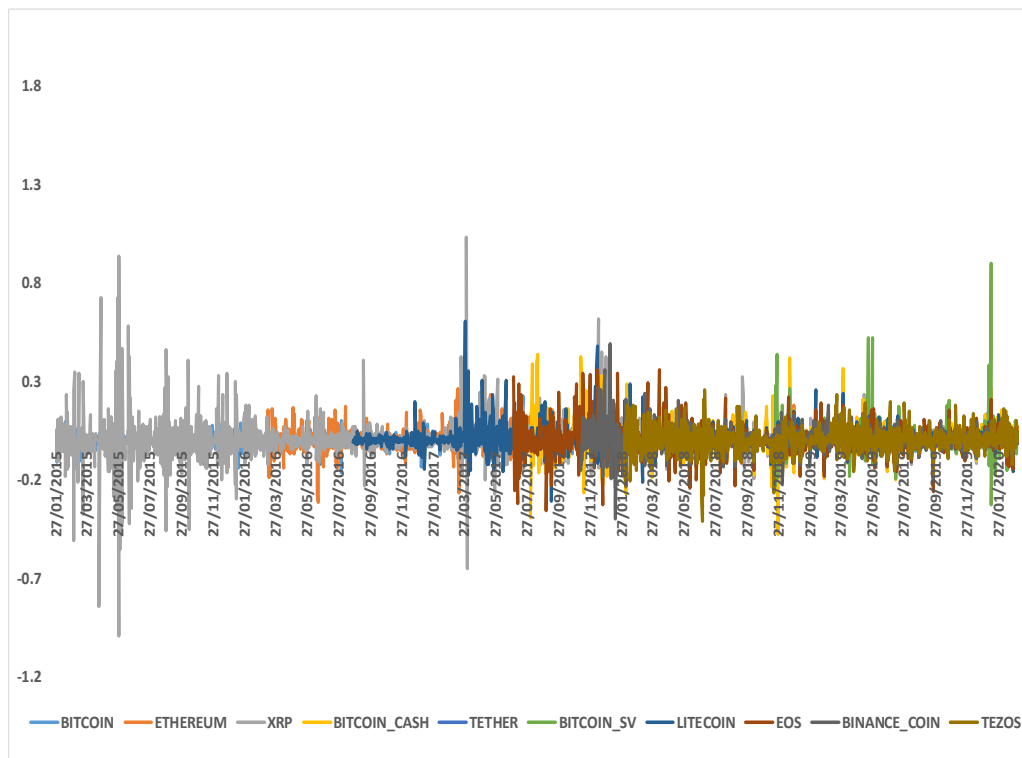
Figure 1. Time evolution of the Bitcoin and the rest of relevant cryptocurrencies daily prices (Bitcoin prices in the right-axis and the rest of cryptocurrencies prices in the left-axis).

Figure 2 shows the time evolution of the cryptocurrency returns and Table 2 collects the descriptive statistics and unit root tests of the ten cryptocurrency returns for daily, weekly, and monthly frequency data. All cryptocurrencies show similar mean log returns, although Bitcoin_sv and Binance_coin show slightly higher mean values. Additionally, the lower the frequency of data, the higher the mean log returns and the higher the standard deviation. Most of cryptocurrency returns show positive skewness, except for Tezos which shows the largest negative skewness for all three data frequencies. All variables show excess kurtosis, especially for daily returns. The standard Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) stationarity test confirms that all cryptocurrency returns are stationary. However, for monthly data, it is interesting to note the smaller sample size for some cryptocurrencies that leads to some doubt about the stationarity of Theter and Tezos returns.

Table 2. Descriptive statistics of Bitcoin returns and returns of the rest of the top ten cryptocurrency returns. [1]

Name	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	JB Stat.	ADF Stat.	PP Stat.	KPSS Stat.
Panel A: Daily Frequency.											
Bitcoin returns	0.0019	0.0019	0.2276	−0.1869	0.0376	−0.1471	7.3114	1453 ***	−43.873 ***	−43.881 ***	0.1581
Ethereum returns	0.0021	−0.0001	0.2586	−0.3134	0.0574	−0.0418	6.4015	703.3 ***	−38.679 ***	−38.816 ***	0.3182
XRP returns	0.0015	−0.0013	1.0280	−0.9965	0.0994	0.8984	30.2463	58000 ***	−32.003 ***	−59.811 ***	0.1527
Bitcoin_cash returns	0.0001	−0.0038	0.4355	−0.4792	0.0780	0.6110	10.6729	2382 ***	−28.553 ***	−28.566 ***	0.1053
Theter returns	0.0000	0.0000	0.0453	−0.0575	0.0063	0.0252	19.1176	11441 ***	−22.254 ***	−47.324 ***	0.0110
Bitcoin_sv returns	0.0026	−0.0014	0.8979	−0.3259	0.0860	3.6652	34.7653	20990 ***	−23.548 ***	−23.516 ***	0.0578
Litecoin returns	0.0022	−0.0024	0.6070	−0.3080	0.0619	1.7426	16.6638	10696 ***	−36.409 ***	−36.453 ***	0.3425
EOS returns	0.0003	−0.0015	0.3559	−0.3567	0.0757	0.4055	7.6595	912.4 ***	−32.951 ***	−32.980 ***	0.0918
Binance_coin returns	0.0028	0.0007	0.4874	−0.4023	0.0626	0.9070	13.6192	4105.6 ***	−27.227 ***	−27.191 ***	0.2255
Tezos returns	0.0000	−0.0042	0.2525	−0.4094	0.0667	−0.1728	6.4442	381.4 ***	−26.555 ***	−26.563 ***	0.3154
Panel B: Weekly Frequency.											
Bitcoin returns	0.0136	0.0093	0.3446	−0.3686	0.1007	−0.0770	4.9667	43.128 ***	−15.549 ***	−15.547 ***	0.1537
Ethereum returns	0.0138	0.0083	0.7457	−0.3951	0.1592	0.9938	6.4246	135.227 ***	−12.899 ***	−13.087 ***	0.2326
XRP returns	0.0103	−0.0124	1.2546	−0.9822	0.2240	1.7314	12.631	1161.02 ***	−16.056 ***	−16.074 ***	0.1336
Bitcoin_cash returns	0.0005	−0.0087	0.8526	−0.7188	0.2199	0.7793	6.1413	68.656 ***	−10.451 ***	−10.422 ***	0.1020
Theter returns	0.0004	0.0001	0.0439	−0.0444	0.0105	−0.4256	8.2501	176.799 ***	−8.8943 ***	−14.437 ***	0.1301
Bitcoin_sv returns	0.0216	−0.0036	0.9894	−0.4649	0.2205	1.6966	8.6941	122.655 ***	−7.6877 ***	−7.6881 ***	0.0484
Litecoin returns	0.0150	−0.0033	1.1406	−0.3031	0.1828	2.6024	16.126	1528.52 ***	−13.285 ***	−13.310 ***	0.2772
EOS returns	0.0017	−0.0064	0.7216	−0.4452	0.1966	0.5641	3.8327	11.387 ***	−9.8301 ***	−9.8971 ***	0.0679
Binance coin returns	0.0213	0.0102	0.6706	−0.3331	0.1645	1.3036	6.8411	107.756 ***	−10.142 ***	−10.433 ***	0.2077
Tezos returns	0.0016	0.0051	0.4392	−0.6843	0.1690	−0.4786	5.1781	25.471 ***	−8.8875 ***	−8.9152 ***	0.2496
Panel C: Monthly Frequency.											
Bitcoin returns	0.0625	0.0437	0.8826	−0.5717	0.2452	0.7046	4.8384	13.414 ***	−7.6711 ***	−7.6713 ***	0.1204
Ethereum returns	0.0640	0.0000	1.2973	−0.7859	0.4150	0.5850	3.63045	3.4593	−6.2936 ***	−6.3522 ***	0.1704
XRP returns	0.0541	−0.0258	2.0518	−0.5347	0.4546	2.5123	10.569	206.345 ***	−6.2751 ***	−5.1123 ***	0.1214
Bitcoin_cash returns	0.0130	−0.0169	1.3271	−1.5992	0.5085	−0.3969	5.6314	9.4425 ***	−5.3384 ***	−5.3394 ***	0.1039
Theter returns	0.0003	0.0003	0.0302	−0.0441	0.0124	−0.8521	6.8862	25.510 ***	−5.9941 ***	−14.375 ***	0.5000 **
Bitcoin_sv returns	0.1087	0.0293	1.1937	−0.4832	0.4831	1.2566	3.6701	3.9463	−4.7496 ***	−4.7496 ***	0.1259
Litecoin returns	0.0732	0.0373	1.5685	−0.6346	0.3906	1.5518	7.1185	45.431 ***	−5.2324 ***	−5.2614 ***	0.2251
EOS returns	0.0417	0.1166	1.5578	−0.9160	0.5107	0.6028	4.3839	4.3512	−3.9072 ***	−4.5276 ***	0.3110
Binance_coin returns	0.1019	0.0534	1.5514	−0.6107	0.4498	1.2385	5.5057	13.966 ***	−4.3508 ***	−4.7401 ***	0.1590
Tezos returns	0.0073	−0.0174	0.8747	−1.0750	0.4401	−0.1028	3.4300	0.2271	−3.6817 **	−3.6335 **	0.2478

[1] This table presents the descriptive statistics of daily (Panel A), weekly (Panel B) and monthly (Panel C) Bitcoin returns and returns of the rest of relevant cryptocurrencies over the period from January 2015 to March 2020. They include mean, median, minimum (Min.) and maximum (Max.) values, standard deviation (Std. Dev.) and Skewness and Kurtosis measures. JB denotes the statistic of the Jarque–Bera test for normality. The results of the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests and the Kwiatkowski et al. (KPSS) stationarity test are also reported in the last three columns. As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.
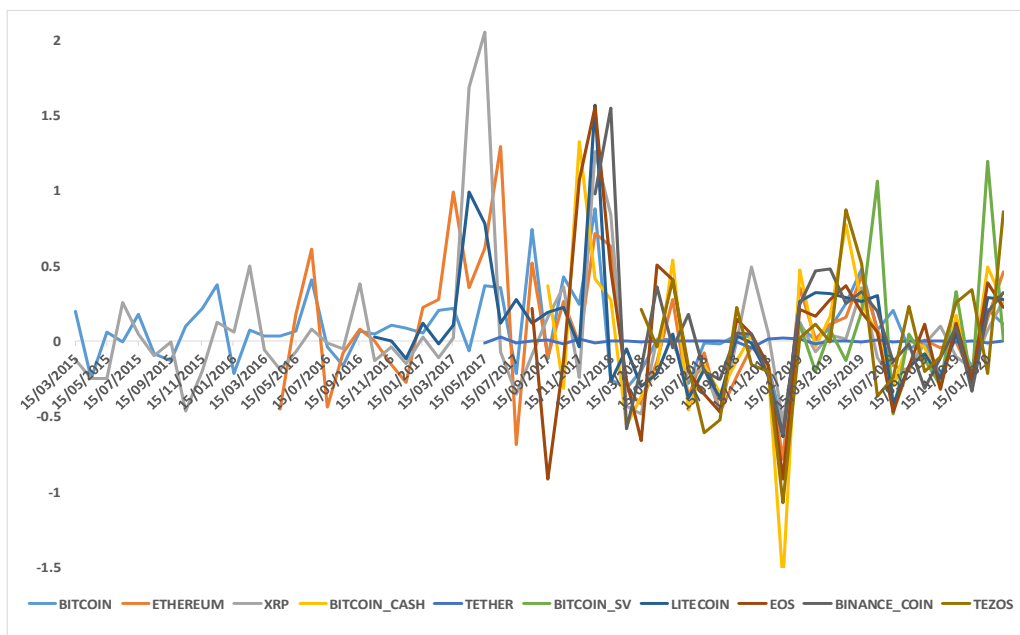
Panel A: Daily frequency
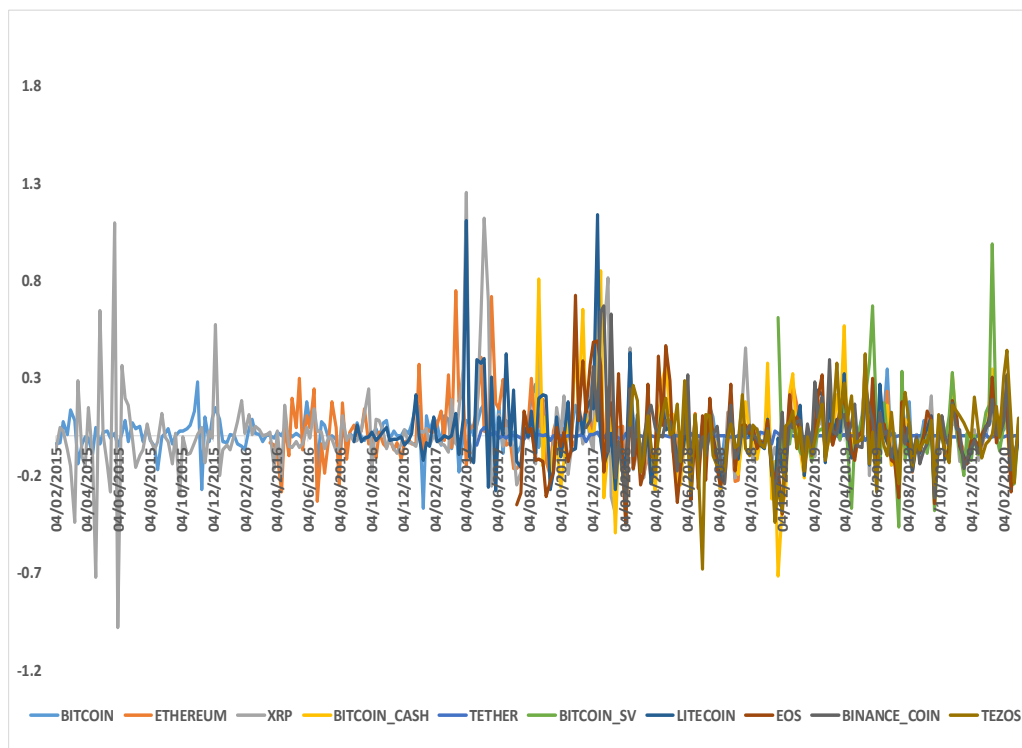
Panel B: Weekly frequency

Figure 2. *Cont.*

Panel C: Monthly frequency

Figure 2. Time evolution of the Bitcoin returns and the rest of relevant cryptocurrency returns. Compiled by the authors, based on the information provided by the *Coinmarketcap* website.

3.2. Methodology

To analyze the connectedness between Bitcoin returns and returns of the other top nine cryptocurrencies we use the nonlinear autoregressive distributed lag (NARDL) model developed by [40]. Importantly, NARDL is applied to simultaneously capture both long- and short-run asymmetries between our variables.

The asymmetric long-run regression of the top ten cryptocurrency returns [18,40] is a simple approach to modelling asymmetric cointegration based on partial sum decompositions:

$$R_{jt} = \alpha_0 + \alpha^+ \cdot BR_t^+ + \alpha^- \cdot BR_t^- + \varepsilon_{jt} \tag{1}$$

$$\Delta BR_t = v_t \tag{2}$$

where R_{jt} and BR_t are scalar I(1) variables. In detail, R_{jt} is the returns from the *j*-th alternative cryptocurrency returns corresponding to period *t*, for $j = 1, \ldots 9$, BR_t is the Bitcoin returns for period *t* which is decomposed as $BR_t = BR_0 + BR_t^+ + BR_t^-$, where BR_t^+ and BR_t^- are partial sums of positive (appreciations) and negative (depreciations) changes in Bitcoin returns, ε_{jt} and v_t are random disturbances and $\alpha = (\alpha_0, \alpha^+, \alpha^-)$ is a vector of long-run parameters to be estimated.

$$BR_t^+ = \sum_{i=1}^{t} \Delta BR_i^+ = \sum_{i=1}^{t} \max(\Delta BR_i, 0) \tag{3}$$

$$BR_t^- = \sum_{i=1}^{t} \Delta BR_i^- = \sum_{i=1}^{t} \min(\Delta BR_i, 0) \tag{4}$$

The coefficients α^+ and α^-, in Equation (1), capture the long-run relationship between each of the top alternative cryptocurrency returns and increases (α^+) or decreases (α^-), respectively, in the Bitcoin returns. Finally, we study whether the long-run relationship reflects asymmetric long-run Bitcoin returns passthrough to each of the alternative cryptocurrency returns.

Reference [40] affirms that the long-run relationship between R_{jt} and BR_t is modelled as piecewise asymmetric linear function subject to the decomposition of BR_t because if we suppose that $|\alpha^+| < |\alpha^-|$ in Equation (1), the long-run effect of a unit negative change in BR_t will increase BR_t by a greater amount than a unit positive change would reduce it. Therefore, reference [40] confirms that the NARDL model includes a regime-switching cointegrating relationship in which regime transitions are governed by the sign of ΔBR_t.

Thus, reference [40] developed the following flexible, dynamic, asymmetric, and nonlinear ARDL(p,q) model by extending the well-known linear autoregressive distributed lag (ARDL) bounds testing approach popularized by [41,42]:

$$R_{jt} = \beta_0 + \beta_1 \cdot R_{t-1} + \beta_2 \cdot BR_t^+ + \beta_3 \cdot BR_t^- + \sum_{i=1}^{p} \phi_i R_{t-i} + \sum_{i=0}^{q} (\gamma_i^+ \Delta BR_{t-i}^+ + \gamma_i^- \Delta BR_{t-i}^-) + \varepsilon_{jt} \tag{5}$$

where BR_t is a k × 1 vector of multiple regressors defined such that $BR_t = BR_0 + BR_t^+ + BR_t^-$, ϕ_i is the autoregressive parameter, p is the number of lagged dependent variables and q is the number of lags for regressors, γ_i^+ and γ_i^- are the asymmetric distributed lag parameters, and, finally, ε_{jt} is an iid process with zero mean and constant variance σ_ε^2.

Moreover, $\alpha^+ = -\beta_2/\beta_1$, $\alpha^- = -\beta_3/\beta_1$, are the coefficients of long-run impacts of Bitcoin return increases and decreases respectively on each of the nine alternative cryptocurrency returns. On the other hand, $\sum_{i=0}^{q} \gamma_i^+$ and $\sum_{i=0}^{q} \gamma_i^-$ measure the short-run influences of increases and decreases respectively of Bitcoin returns on each of the top nine alternative cryptocurrency returns. Thus, not only are the asymmetric long-run relationship considered, but the asymmetric short-run influences of Bitcoin returns changes on the top ten cryptocurrency returns are also captured in order to identify differences in the response of economic agents to positive and negative shocks.

Reference [40] affirms that the dynamic adjustment of the NARDL model in the error correction form maps the gradual movement of the process from initial equilibrium through the shock and towards the new equilibrium. Moreover, the estimation of the error correction model (ECM) improves the performance of the NARDL model in small samples and increase the power of the cointegration tests. Thus, we estimate the proposed NARDL model using stepwise regression under ECM.

In summary, the cointegrating NARDL model of reference [40] enables us to check for the possibility that the time series are nonlinearly cointegrated. This methodology tests simultaneously the long- and short-run asymmetries estimating positive and negative partial sum decompositions of the regressors in a computationally simple and tractable manner that reflects its flexibility. Additionally, it also measures the separate responses to positive and negative shocks of the regressors from the asymmetric dynamic multipliers. Moreover, references [2,18,19] suggest, in addition to the advantages of good small sample properties and simultaneous estimates of short- and long-run coefficients, some additional advantages of the NARDL methodology including suitable regardless of the stationarity of the variables and freedom of residual correlation and so not prone to omitted lag bias.

However, empirical implementation of the NARDL approach requires classical unit root tests in order to confirm that the variables are I(0) or I(1), because the presence of an I(2) variable renders the computed F statistics for testing cointegration invalid. These tests, collected in Table 2, confirm that all cryptocurrency returns are stationary for daily and weekly data although there are doubts about the stationary of Theter and Tezos for monthly data due to the low number of data for these recent cryptocurrencies.

Finally, based on the estimated NARDL model, we test for the presence of asymmetry and cointegration in the relations between Bitcoin returns and the rest of the top ten cryptocurrencies. Specifically, we study in the next section: first, the connectedness between these variables by the Pearson's correlation coefficients defined by the null hypothesis of no correlation (H_0: $PCorr = 0$); second, the presence of cointegration by the Wald F test for the joint null hypothesis that coefficients on the level variables are jointly equal to zero (H_0: $\beta_1 = \beta_2 = \beta_3 = 0$); third, the cointegration equation

(long-run elasticities) between variables; fourth, the long-run symmetry by means of the Wald test, with symmetry implying H_0: $-\beta_2/\beta_1 = -\beta_3/\beta_1$; fifth, the short-run symmetry in the short-run model by the Wald test for the null of short-run symmetry defined by $\gamma_i^+ = \gamma_i^-$ and sixth, the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for 1 to 4 lags on the rest of cryptocurrencies' returns.

4. Results and Discussion

This section reports the estimates of the nonlinear ARDL model; including estimates of the long- and short-run relationships between Bitcoin returns and the rest of the top 10 cryptocurrency returns for different frequencies (daily, weekly, and monthly) for a sample period from 26 January 2015 to 7 March 2020. We would like to highlight that the results may not be appropriate for monthly frequencies because due to the recent appearance of certain currencies such as "Bitcoin SV" (on 19 November 2018) and "Tezos" (on 2 February 2018), there are very few monthly data in these two cases. In addition, it is noteworthy that the maximum lag order considered in these NARDL estimations is 4.

4.1. Results of the NARDL Models: Daily Frequency

Table 3 reports the regression results of the nonlinear ARDL models and the asymmetry and cointegration tests between Bitcoin returns and the rest of the top ten cryptocurrency returns (Ethereum, XRP, Bitcoin Cash, Tether, Bitcoin SV, Litecoin, EOS, Binance coin, and Tezos) for daily frequency. Table 3 is organized as follows. Column 2 contains the Pearson's correlation coefficients, column 3 the Wald F test for the presence of cointegration, column 4 the cointegration equation (long-run elasticities) between Bitcoin returns and the rest of cryptocurrency returns, column 5 the Wald test for long-run symmetry, column 6 the Wald test for short-run symmetry, columns 7 and 8 report the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for (1–4)-lags on the rest of cryptocurrencies and finally, column 9 shows the Adjusted R^2 of each cryptocurrency.

The Pearson's correlation coefficients in column 2 show that the null hypothesis of no correlation (H_0: PCorr = 0) is rejected by all the top ten cryptocurrencies. More specifically, a high positive correlation is observed between Bitcoin returns and all the rest of the top ten cryptocurrency returns. All of them exhibit statistical significance at the 1% level, showing Pearson's correlation coefficients between 43.3% and 82.2%, except for Tether that shows statistical significance at the 5% level and the lowest Pearson's correlation coefficient of 10.7%.

The Wald F test for the presence of cointegration reported in column 3 shows that the null hypotheses of no cointegration on the level variables jointly equal to zero (H_0: $\beta_1 = \beta_2 = \beta_3 = 0$) is rejected by five cryptocurrencies (XRP, Bitcoin_cash, Tether, EOS, and Binance coin). Thus, the F statistics show long-run relationships, i.e., cointegration, between changes in Bitcoin returns and XRP, Bitcoin_cash, Tether, EOS and Binance_coin returns for daily frequency. Additionally, the long-run coefficients of changes in Bitcoin returns are positive and statistically significant at 1% level for these five cryptocurrencies, where the highest values are for XRP and Theter.

Column four of Table 3 shows the cointegration equation: $R_{jt-i} = e^+ \cdot BR^+_{t-i} + e^- \cdot BR^-_{t-i}$ (long-run elasticities) between Bitcoin returns (BR) and the rest of the top ten cryptocurrencies' returns (R_{jt-i}). Thus, regarding the long-run elasticities for the cumulative sum of positive changes in Bitcoin returns) BR^+_{t-i} and the cumulative sum of negative changes in Bitcoin returns BR^-_{t-i}, all cryptocurrency returns respond in the same way to positive and negative changes in Bitcoin returns. Additionally, the coefficients are quite similar and are of modest size for all cryptocurrencies. The largest coefficients correspond to Bitcoin_sv returns that respond more to positive and negative changes in Bitcoin returns (4.5% versus 5.7%, respectively). Moreover, the long-run elasticities for the cumulative sum of positive and negative changes in Bitcoin returns are statistically significant just for four cryptocurrencies, EOS, XRP, Tether and Binance_coin. Moreover, the coefficients are negative for XRP and EOS, meaning they move in the opposite direction to the changes in Bitcoin returns, but are positive for Tether and Binance_coin, meaning they fluctuate in line with Bitcoin returns.

Table 3. Regression results of nonlinear ARDL models: asymmetry and cointegration tests between Bitcoin returns and the rest of relevant cryptocurrencies' returns: daily frequency. [1]

Cryptocurrencies	PCorr	Coint	Eq	LAsym	SAsym	Lags$^+$	Lags$^-$	Adj. R^2
Ethereum returns	0.8242 ***	0.6334	e^+: 0.0370 e^-: 0.0500	0.3384	17.776 ***	(2): 0.0935 * (4): 0.1477 ***	(3): −0.1319 **	0.3254
XRP returns	0.7266 ***	60.617 ***	e^+: −0.0226 ** e^-: −0.0272 **	3.3268 *	8.1825 ***	(1): 0.2196 ** (3): 0.1807 **	-	0.1619
Bitcoin_cash returns	0.6778 ***	15.534 ***	e^+: 0.0203 e^-: 0.0230	0.8904	13.737 ***	(1): −0.1787 **	(1): −0.3240 ***	0.3091
Theter returns	0.1069 **	54.861 ***	e^+: 0.0019 ** e^-: 0.0020 *	0.2310	-	-	(1): −0.0124 * (2): −0.0224 ***	0.1449
Bitcoin_sv returns	0.4328 ***	0.3960	e^+: 0.4491 e^-: 0.5710	0.2313	6.7191 ***	(2): 0.3620 **	-	0.1824
Litecoin returns	0.7694 ***	0.6729	e^+: −0.0390 e^-: −0.0550	0.4228	18.475 ***	(1): 0.1033 * (2): 0.1408 **	-	0.3601
EOS returns	0.7609 ***	5.7063 ***	e^+: −0.4973 *** e^-: −0.5148 ***	0.9959	18.881 ***	-	(4): −0.2319 ***	0.4045
Binance_coin returns	0.6222 ***	10.605 ***	e^+: 0.0561 * e^-: 0.0668 **	3.9280 **	17.722 ***	-	(1): −0.3004 ***	0.4023
Tezos returns	0.5006 ***	1.0487	e^+: 0.1403 e^-: 0.1275	0.3006	10.531 ***	-	-	0.1936

[1] This table reports the coefficient estimates of the NARDL model between Bitcoin returns and the rest of relevant cryptocurrencies' returns. PCorr refers to the Pearson's correlation coefficients defined by the null of $PCorr = 0$. Coint refers to the Wald test for the presence of cointegration defined by $\beta_1 = \beta_2 = \beta_3 = 0$. Eq shows the cointegration equation (long-run elasticities) between Bitcoin returns (*BR*) and the rest of relevant cryptocurrencies' returns $R_{jt\text{-}i} = e^+ \cdot BR^+_{t\text{-}i} + e^- \cdot BR^-_{t\text{-}i}$. LAsym refers to the Wald test for the null of long-run symmetry defined by $-\beta_2/\beta_1 = -\beta_3/\beta_1$. SAsym refers to the Wald test for the null of short-run symmetry defined by $\gamma_i^+ = \gamma_i^-$. Lags$^+$ and Lags$^-$ show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for ()-lags on the rest of relevant cryptocurrency returns. As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in [43], in case of small sample size.

The fifth column shows the Wald test for investigating long-run symmetry. These results show that the null hypothesis of long-run symmetry (H_0: $-\beta_2/\beta_1 = -\beta_3/\beta_1$), is rejected only by two cryptocurrencies: XRP and Binance_coin. Thus, the Wald test indicates that there could be asymmetry in the long-run impact of Bitcoin returns on XRP and Binance_coin returns for daily data, corroborating previous results obtained with long-run elasticities.

The sixth column shows the Wald test for short-run symmetry. In this case, the null hypothesis of short-run symmetry (H_0: $\gamma_i^+ = \gamma_i^-$), is rejected by all the cryptocurrencies as all cryptocurrencies show positive and statistically significant coefficients at the 1% significance level. Therefore, there is strong evidence of asymmetric short-run responses of all cryptocurrency returns to changes in Bitcoin returns for daily frequency. Thus, nonlinear asymmetries are important in the short-run relationship between Bitcoin returns and the remaining top ten cryptocurrencies' returns for daily data.

Columns seven and eight show the effect of the cumulative sum of positive and negative changes respectively in Bitcoin returns for 1 to 4 lags on the rest of cryptocurrencies' returns. In line with [2,18], among others, we observe high persistence in the effect of both positive and negative changes in Bitcoin returns, for 1 to 4 lags, in more than half of the cryptocurrency returns. More specifically, we observe a positive and statistically significant effects of the cumulative sum of positive changes in Bitcoin returns on Ethereum returns (for 2- and 4-lags), XRP returns (for 1- and 3-lags), Bitcoin_sv returns (for 2-lags) and Litecoin returns (for 1- and 2-lags), as well as a negative and statistically significant effect of the cumulative sum of positive changes in Bitcoin returns on Bitcoin_cash returns (for 1-lag). We also notice just negative and statistically significant effect of the cumulative sum of negative changes in Bitcoin returns on Ethereum returns (for 3-lags), Bitcoin_cash returns (for 1-lag), Tether returns (for 1- and 2-lags), EOS returns (for 4-lags) and Binance_coin returns (for 1-lag).

Finally, the explanatory power of the NARDL model as reported in the last column varies from a minimum of 14.5% for Tether to a maximum of more than 40% for EOS and Binance_coin returns.

4.2. Results of the NARDL Models: Weekly Frequency

Table 4 shows the weekly regression results of nonlinear ARDL models and asymmetry and cointegration tests between Bitcoin and the remaining top 10 cryptocurrency returns. Overall, the explanatory power of the NARDL model as measured and reported in the last column of Table 4 varies from a minimum of 6.7% (for XRP returns) to a maximum of 51.6% (for Bitcoin_cash returns) and 50% (for EOS returns). There appears to be a tendency for the R^2 to be a bit higher for weekly than for daily frequencies.

Table 4, column 2, reports the Pearson's correlation coefficients between Bitcoin returns and the rest of the top ten cryptocurrency returns and states that the null hypothesis of no correlation is rejected by all the top ten cryptocurrencies. There is a strong positive correlation, at least 40%, between Bitcoin and all but Tether cryptocurrency returns and all of them show a statistical significance at the 1% level. Tether is an interesting exception showing a negative and statistically significant correlation with Bitcoin returns.

Column 3's Wald's F test for cointegration shows that the null hypothesis of no cointegration is rejected by four cryptocurrencies (Ethereum, Tether, EOS, and Binance coin). Thus, indicating long-run connectedness between weekly Bitcoin returns and Ethereum, Tether, EOS and Binance_coin weekly returns. Additionally, the long-run coefficients of changes in Bitcoin returns are positive and significant at the 5% significance level for Tether and EOS and at the 10% significance level for Ethereum and Binance_coin.

Table 4. Regression results of nonlinear ARDL models: asymmetry and cointegration tests between Bitcoin returns and the rest of relevant cryptocurrencies' returns: weekly frequency. [1]

Cryptocurrencies	PCorr	Coint	Eq	LAsym	SAsym	Lags$^+$	Lags$^-$	Adj. R^2
Ethereum returns	0.8123 ***	2.3692 *	e^+: 0.0529 e^-: 0.0821	0.3332	6.9406 ***	-	-	0.3861
XRP returns	0.7392 ***	0.8958	e^+: −1.1248 * e^-: −1.7386 *	0.2152	3.5334 ***	-	-	0.0666
Bitcoin_cash returns	0.7315 ***	0.5972	e^+: −0.9784 e^-: −1.0266	0.0613	6.8692 ***	(2): 0.3845 ** (4): 0.3768 *	(1): 0.5360 ** (3): 0.7716 ***	0.5155
Theter returns	−0.4073 ***	2.8918 **	e^+: 0.0388 *** e^-: 0.0429 ***	0.6522	-	(1): 0.0440 *** (3): 0.0196 *	-	0.1409
Bitcoin_sv returns	0.4208 ***	1.0911	e^+: −0.7533 e^-: −1.4758	0.6861	2.6063 ***	(1): 0.8402 **	(1): −1.0168 **	0.2719
Litecoin returns	0.6745 ***	0.2642	e^+: 0.0899 e^-: −0.0127	0.1199	5.3563 ***	-	-	0.3196
EOS returns	0.6991 ***	3.1813 **	e^+: 0.6927 ** e^-: 0.8068 **	0.7554	7.7183 ***	(3): −0.5188 ***	(1): −0.4054 ***	0.5000
Binance_coin returns	0.5308 ***	1.9915 *	e^+: 0.1923 e^-: 1.1908	0.0867	6.2489 ***	(2): 0.4735 ***	-	0.3054
Tezos returns	0.5138 ***	0.9228	e^+: 0.5929 e^-: 0.4970	0.2075	6.2904 ***	-	-	0.2798

[1] This table reports the coefficient estimates of the NARDL model between Bitcoin returns and the rest of relevant cryptocurrencies' returns. PCorr refers to the Pearson's correlation coefficients defined by the null of *PCorr* = 0. Coint refers to the Wald test for the presence of cointegration defined by $\beta_1 = \beta_2 = \beta_3 = 0$. Eq shows the cointegration equation (long-run elasticities) between Bitcoin returns (*BR*) and the rest of relevant cryptocurrencies' returns $R_{j-i} = e^+ \cdot BR^+_{t-i} + e^- \cdot BR^-_{t-i}$. LAsym refers to the Wald test for the null of long-run symmetry defined by $-\beta_2/\beta_1 = -\beta_3/\beta_1$. SAsym refers to the Wald test for the null of short-run symmetry defined by $\gamma_i^+ = \gamma_i^-$. Lags$^+$ and Lags$^-$ show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for ()-lags on the rest of relevant cryptocurrency returns. As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in [43], in case of small sample size.

Column four of Table 4 shows that all cryptocurrency returns (except for Litecoin returns) respond in the same way to positive and negative changes in Bitcoin returns. Additionally, the coefficients are quite similar for most cryptocurrencies except for Ethereum, Bitcoin_sv, Litecoin and especially for Binance_coin where estimates for long-run elasticities are substantially different. Clearly, the Binance_coin returns respond more to negative changes in Bitcoin returns because the coefficient is larger. Thus, for instance, a 10% increase in Bitcoin returns is related to the increase in the Binance_coin returns by about 1.9%. However, a 10% decrease in Bitcoin returns leads to an 11.9% decrease in Binance_coin returns. Nevertheless, these elasticities are not statistically significant. Long-run elasticities for the cumulative sum of positive and negative changes in Bitcoin returns are statistically significant just for Tether, EOS and XRP at the 1%, 5% and 10% significance level, respectively. Moreover, the coefficients are negative for XRP and positive for EOS and Tether.

The Wald test for long-run symmetry reported in column five shows that the null hypothesis of long-run symmetry is not rejected by any of the top ten cryptocurrencies. However, the corresponding test for short-run symmetry reported in column six shows that the null hypothesis of short-run symmetry is rejected by all the cryptocurrencies. More specifically, all cryptocurrencies show positive and statistically significant coefficients at 1% significance level. Therefore, there is strong evidence of asymmetric short-run responses of all cryptocurrency returns to changes in Bitcoin returns for weekly frequency but there is no evidence of long-run asymmetry. Therefore, nonlinear asymmetries are also important for the short-run relationship between Bitcoin and the remaining top 10 cryptocurrencies for weekly data.

Weekly frequency data also corroborate a high persistence on the impact of both positive and negative changes in Bitcoin returns, for 1 to 4 lags, on half of the remaining top 10 cryptocurrency returns. More specifically, the cumulative sum of positive and negative changes (respectively) of Bitcoin returns for 1 to 4 lags on the rest of cryptocurrency returns, shown in columns seven and eight of Table 4, illustrates that there is a statistically significant and slightly larger short-run impact of increases than decreases of Bitcoin returns on most cryptocurrency returns. We notice a positive and statistically significant effect of the cumulative sum of positive changes in Bitcoin returns on Bitcoin_cash returns for 2- and 4-lags, on Tether returns for 1- and 3-lags, on Bitcoin_sv returns for 1-lag and on Binance_coin returns for 2-lags, as well as a negative and statistically significant effect of the cumulative sum of positive changes in Bitcoin returns on EOS returns for 3-lags. We also notice a positive and statistically significant effect of the cumulative sum of negative changes in Bitcoin returns on Bitcoin_cash for 1- and 3-lags and a negative and statistically significant effect of the cumulative sum of negative changes in Bitcoin returns on Bitcoin_sv and EOS for 1-lag.

4.3. Results of the NARDL Models: Monthly Frequency

Table 5 shows the regression results of nonlinear ARDL models and asymmetry and cointegration tests between Bitcoin returns and the remaining top 10 cryptocurrency returns for monthly frequency. It should be noted that monthly data may give inaccurate results for a few of the altcoin cryptocurrencies because some have only recently been created and so have a modest number of monthly observations. Specifically, the most recent cryptocurrencies are Tezos, whose prices start on 2 February 2018, and especially Bitcoin_sv, whose prices start on 19 November 2018. Therefore, we will analyze the monthly results considering this potential limitation.

Neglecting the results of recently issued cryptocurrencies with modest sample size, the explanatory power of the monthly NARDL model varies from a minimum adjusted R^2 of 26.8% for the Tether returns to a maximum of 77.3% for EOS returns. It is noticeable that the two most recently issued cryptocurrencies with the smallest sample size have the highest adjusted R^2; 96.6% for Bitcoin_sv and 80.1% for Tezos. In any event, there is a clear tendency for the explanatory power of the NARDL model to rise as the sampling frequency decreases. For example, for EOS the explanatory power steadily increases as we move from daily, weekly, and monthly frequency, achieving R^2 of 40.4%, 50% and 77.3% respectively.

Table 5. Regression results of nonlinear ARDL models: asymmetry and cointegration tests between Bitcoin returns and the rest of relevant cryptocurrencies' returns: monthly frequency. [1]

Cryptocurrencies	PCorr	Coint	Eq	LAsym	SAsym	Lags$^+$	Lags$^-$	Adj. R^2
Ethereum returns	0.6352 ***	0.1902	e^+: −0.8061 e^-: −1.0821	0.0205	3.9753 ***	-	-	0.4302
XRP returns	0.4454 *	4.4249 ***	e^+: 0.1575 e^-: 0.4109	0.9089	2.7308 ***	-	-	0.2721
Bitcoin_cash returns	0.5927 **	0.4673	e^+: 0.7670 e^-: 0.4763	0.1481	4.8457 ***	(1): 1.1441 ***	-	0.5652
Theter returns	−0.1473	3.8636 **	e^+: 0.0203 ** e^-: 0.0289 **	1.8779	−2.5775 **	(1): 0.0210 **	(1): −0.0292 *	0.2680
Bitcoin_sv returns	0.2854	34.743 ***	e^+: 0.7260 e^-: 6.0939 *	46.084 ***	−3.2676 ***	(1): 2.8139 * (2): 2.4948 *	-	0.9657
Litecoin returns	0.4924 *	2.7840 **	e^+: 3.0736 *** e^-: 4.2521 **	0.1822	3.4526 ***	(1): 0.7763 ** (4): 0.8604 ***	(3): −0.6674 *	0.4907
EOS returns	0.4932 *	2.7137 *	e^+: 1.4434 e^-: 2.6779 **	0.3991	3.2146 ***	(1): 0.8562 ***	(1): −1.0826 ** (3): −0.7961 ***	0.7731
Binance_coin returns	0.5057 *	1.8156	e^+: 0.2134 e^-: 0.2746	0.0705	2.4323 ***	(1): 1.3610 *** (4): 0.3091 *	(2): −0.6275 ** (3): −1.1079 *** (4): −0.6770 **	0.7481
Tezos returns	0.2630	14.1765 ***	e^+: 1.5210 *** e^-: 3.2410 ***	20.439 ***	3.0335 ***	(2): −2.1163 ***	(1): 3.5387 *** (2): 2.1296 *** (3): 1.9299 ***	0.8079

[1] This table reports the coefficient estimates of the NARDL model between Bitcoin returns and the rest of relevant cryptocurrencies' returns. PCorr refers to the Pearson's correlation coefficients defined by the null of *PCorr* = 0. Coint refers to the Wald test for the presence of cointegration defined by $\beta_1 = \beta_2 = \beta_3 = 0$. Eq shows the cointegration equation (long-run elasticities) between Bitcoin returns (*BR*) and the rest of relevant cryptocurrencies' returns $R_{jt-i} = e^+ \cdot BR^+_{t-i} + e^- \cdot BR^-_{t-i}$. LAsym refers to the Wald test for the null of long-run symmetry defined by $-\beta_2/\beta_1 = -\beta_3/\beta_1$. SAsym refers to the Wald test for the null of short-run symmetry defined by $\gamma_i^+ = \gamma_i^-$. Lags$^+$ and Lags$^-$ show the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for ()-lags on the rest of relevant cryptocurrency returns. As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in [43], in case of small sample size.

The Pearson's correlation reported in column two of Table 5 rejects the null hypothesis of no correlation for just six out of nine cryptocurrencies. More specifically, a positive and statistically significant relationship is observed between Bitcoin returns and Ethereum Bitcoin_cash, XRP, Litecoin, EOS and Binance_coin returns at but only Ethereum and Bitcoin_cash are highly significant, the rest are significant at the 10% level. It is interesting to note that the three cryptocurrencies that do not reject the null hypothesis are the two above noted most recently issued cryptocurrencies and Tether, which as the lowest R^2 of all, showing that there is no correlation between bitcoin returns and the returns of these more recent cryptocurrencies.

The results of the Wald's F test for cointegration, reported in column three of Table 5, show that the null hypothesis of no cointegration is rejected by six cryptocurrencies, XRP, Tether, Bitcoin_sv, Litecoin, EOS, and Tezos. Thus, the bounds F statistics show long-run connectedness between these cryptocurrency returns and changes in Bitcoin returns. In addition, the long-run coefficients of changes in Bitcoin returns are positive and statistically significant in these six cryptocurrencies. We should note that for Tezos and Bitcoin_sv, the two most recently issued cryptocurrencies, have the very high F statistics that could be an artifact of a modest sample size.

The cointegration equation listed in column four shows that all cryptocurrency returns respond in the same way to positive and negative changes in Bitcoin returns. Additionally, the coefficients are quite similar for most cryptocurrencies except for the two most recently issued cryptocurrencies where Tezos coefficient of negative changes in Bitcoin returns is twice as high as the coefficient of positive changes and especially the most recently issued Bitcoin_sv, where the coefficient of negative changes is almost nine times higher than the coefficient of positive changes. Furthermore, the long-run elasticities for the cumulative sum of positive and negative changes in Bitcoin returns are statistically significant just for Tether, Litecoin and Tezos and just the coefficient of negative changes of Bitcoin returns for Bitcoin_sv and EOS.

The results of the Wald test for testing the long-run symmetry reported in column five, show that the null hypothesis of long-run symmetry is rejected only by Bitcoin_sv and Tezos indicating that there could be asymmetry in the long-run impact of Bitcoin returns for these two most recently issued cryptocurrencies. For the Wald test for testing the short-run symmetry reported in column six, it is observed that only two of them, one of which is the modest sample size by Bitcoin_sv, show negative and statistically significant coefficients. Meanwhile all the remaining cryptocurrencies have positive and statistically significant coefficients at 1% level. Therefore, all cryptocurrency returns show asymmetric short-run responses to changes in Bitcoin returns for monthly frequency.

The effect of the cumulative sum of positive and negative changes in Bitcoin returns for 1–4 lags on the rest of cryptocurrency returns is shown in columns seven and eight of Table 5. There is a positive and statistically significant effect for the cumulative sum of positive changes in Bitcoin returns on six out of nine cryptocurrency returns: on Bitcoin_cash, Tether and EOS returns (for 1-lag), on Bitcoin_sv returns (for 1- and 2-lags), and on Litecoin and Binance_coin returns (for 1- and 4-lags), as well as just a negative and statistically significant effect in Bitcoin returns on Tezos returns (for 2-lags). We also notice a positive and statistically significant effect of the cumulative sum of negative changes in Bitcoin returns just on Tezos returns (for 1-, 2- and 3-lags), as well as a negative and statistically significant effect of the cumulative sum of negative changes in Bitcoin returns on four out of nine cryptocurrency returns: on Tether returns (for 1-lag), on Litecoin returns (for 3-lags), on EOS returns (for 1- and 3-lags) and on Binance_coin returns (for 2-, 3-, and 4-lags). Consequently, for monthly frequency, we find a high persistence in the effect of both positive and negative variations in Bitcoin returns, for 1 to 4 lags, on most of the cryptocurrency returns.

5. Concluding Remarks

This paper aims to study both long- and short-run interdependencies between returns of Bitcoin and the rest of the recent most important cryptocurrencies that is Ethereum, XRP, Bitcoin Cash, Tether, Bitcoin SV, Litecoin, EOS, Binance coin, and Tezos applying a NARDL approach. Our sample period

extends from 26 January 2015 to 7 March 2020 and our research check results for daily, weekly, and monthly frequency data.

To the best of knowledge, this is the first study that explores the co-movement between Bitcoin and the remaining top ten cryptocurrencies selected according to the largest market capitalization, by using the NARDL approach to evaluate both long- and short-run asymmetries. The Pearson's correlation coefficients provide evidence that there is a positive and statistically significant correlation between Bitcoin returns and all the rest of the top ten cryptocurrencies for all frequencies, except for the most recent cryptocurrencies, for monthly frequency, likely due to the lack of data. These results are in line with those obtained in works such as [2,4,9,15,26,31]. We find a cointegration or long-run relationship between most cryptocurrency returns and changes in Bitcoin returns for all frequencies [32], while in [35] most of the variables are not cointegrated. Moreover, the cointegration equation reveals that cryptocurrency returns usually respond in the same way to positive and negative changes in Bitcoin returns, with very few exceptions. Furthermore, our tests indicate that asymmetries in the long-run impact of Bitcoin returns is operative on a maximum of only two of nine cryptocurrency returns but there is strong evidence of asymmetry in the short-run impact of Bitcoin returns in all cryptocurrency returns for all frequencies. This provides strong evidence that nonlinear asymmetries are especially important for the short-run relationships between these cryptocurrencies. Our results are similar to those found in [1,22], but instead of using ARDL, we include non-linearity in the estimation. We find evidence of high persistence in the impact of both positive and negative changes in Bitcoin returns, for 1 to 4 lags for most of the cryptocurrency returns. Specifically, the cumulative sum of positive and negative changes in Bitcoin returns has a statistically significant effect on most cryptocurrency returns for daily, weekly, and monthly frequencies. The NARDL model explains more than 40% and 50% of the cryptocurrency returns with changes in Bitcoin returns for the daily and weekly time series respectively but monthly results for the most recently issued cryptocurrencies could be exaggerated due to the short time series available for monthly data.

According to our results, some cryptocurrencies (in concrete XRP, Tether and EOS) are more connected to Bitcoin than others (Tezos, among other altcoins), in line with [23]. The economic intuition being the more connected an altcoin is, the more likely they can be used as a substitute whereas the lower the connectedness, the more they can be considered to be an alternative asset distinct from Bitcoin. Thus, potential practical applications of our results could be that the least connected virtual coin can be used to diversify positions in Bitcoin whereas the more connected the altcoin is, the better it can be used to hedge positions in Bitcoin. Assuming that there would be a lack of liquidity in the cryptocurrency market so that if you, as a potential investor, wish to reduce exposure in Bitcoin and you sell, then your own selling actions could reduce the Bitcoin price against you. Similarly, if you want to hedge, you probably could not short Bitcoin so selling a highly correlated altcoin could be the alternative to hedge. Moreover, another relevant aspect of research is how the results change as we move from daily to monthly observations. We seem to obtain an increase in R square as we reduce the frequency of the observations. Does that suggest that the longer the periodicity of data the more connected the altcoins are to Bitcoin? That would be interesting if for example we wish to hedge Bitcoin positions with say Tether positions.

For all that, our results would have important implications for market participants, because potential connectedness between the top cryptocurrencies' returns may affect the decision-making of investors and policymakers. Thus, future research could extend our study to the analysis of potential co-movements in volatility in the cryptocurrency market as volatility co-movements can have a key role for implementing suitable investment strategies as well. To make more informed decisions, an extensive study of interdependencies between cryptocurrencies and conventional assets is crucial. Finally, it would be very interesting to incorporate into the analysis the stage of the economy, because previous literature confirms that interdependence patterns may change over time. This is a significant aspect in a market as volatile as the cryptocurrency market, especially in periods of economic recession such as the present one, caused by COVID-19, which is affecting the whole world. Therefore, a critical

issue will be to propose investment strategies using cryptocurrencies as hedging and/or diversification instruments in the current period affected by the SARS-CoV-2 pandemic.

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