Nonlinear autoregressive distributed lag approach: an application on the connectedness between Bitcoin returns and the other ten most relevant cryptocurrencies returns

Short title: Cryptocurrency returns: An asymmetric nonlinear cointegration approach

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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 NARDL (nonlinear autoregressive distributed lag) approach. We find important and positive interdependencies among cryptocurrencies and significant long-run relations 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 cryptocurrencies returns. Thus, our model explains about 50% of the other cryptocurrencies returns with changes in Bitcoin returns.

Keywords: Bitcoin; Cryptocurrencies; NARDL; Connectedness;

JEL classification: G11, G15, O51

1. Introduction

The importance of the cryptocurrency market continues to increase even in recent years. Ciaian et al., (2018) highlighted that the cryptocurrency market was worth more than $12.5 billion in 2016. Other studies, such as Jareño et al. (2020), 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 $4,800 US dollars between Oct. 2016 and Oct. 2017. Nowadays, the overall cryptocurrency market is even more more important as the total cryptocurrency market capitalization is $251.5 billion on March 7, 2020 and the Bitcoin price has increased almost 3300% from $269.2 to $ 8,887.8 US dollars between the beginning (January 26, 2015) and the final (March 7, 2020) date of the sample period.

Furthermore, Bitcoins dominance in the cryptocurrency market is increasing. Bação et al. (2018) confirmed that Bitcoin's capitalization was about 37% of the cryptocurrency market on May 1, 2018 but now, merely two years later, Bitcoin's market share is about 66% on March 7, 2020. Therefore, Bitcoin is the most globally recognised cryptocurrency in terms of capitalization and the number of users. In addition, Papadimitriou et al. (2020) note that the cryptocurrencies' market reached peak in the early 2018 with the market's capitalization of $800 billion and suggest that crypto currencies can now be considered as 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 researches analyse 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: ARDL model in Ciaian et al. (2018); several Diebold and Yilmaz (2009, 2012, 2016) type approaches in Koutmos (2018) and Ji et al. (2019); VAR and GARCH methodologies in Bação et al. (2018), Symitsi and Chalvatzis (2018), Charfeddine et al. (2020) and Walther et al. (2019); BEKK-GARCH framework in Beneki et al. (2019), Katsiampa et al. (2019a and b) and Tu and Xue (2019); and other innovative approaches in Song et al. (2019), Papadimitriou et al. (2020), 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 cryptocurrencies 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 January 26, 2015 to March 7, 2020 in a non-linear 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 crypto currency markets. This is accomplished by using the NARDL approach (Jareño et al., 2019a and 2020) to examine the relationship between Bitcoin returns and the remaining top 10 cryptocurrency returns. Arize et al. (2017) and Jareño et al. (2019a, 2020) 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. In addition, 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 ten alternative named cryptocurrencies. Alternative cryptocurrencies have been selected as the largest market capitalisations as reported on March 7, 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 summarises, presents concluding remarks and remarks on potential implications and future research.

2. Literature review

The number of empirical studies analysing cryptocurrencies has grown exponentially in recent years in the financial literature. Thus, Corbet et al. (2019) perform 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 Jareño et al. (2020) who study the relationship between Bitcoin and Gold price returns, finding a positive and statistically significant connectedness, and White et al. (2020) who remark the prevalence of cryptocurrencies with over 2,000 Bitcoin-like cryptocurrencies now in use amongst many recent contributions.

However, a recent important extension the literature examines the relationships among Bitcoin and other alternative cryptocurrencies. Ciaian et al. (2018) propose the Autoregressive- Distributed-Lag (ARDL) methodology in order 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, Nguyen et al. (2019) check if the new coin events significantly influence Bitcoin returns. They find evidence that IPOs of new altcoins reduce Bitcoin returns.

Mensi et al. (2019) study 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. Kumar and Ajaz (2019) use wavelet-based methods to analyse 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. In addition, 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 crypto-currency prices are driven by Bitcoin price fluctuations, with important implications for investment purposes. Bouri et al. (2020) apply 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. Katsiampa (2019) analyses 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, Koutmos (2018) measures interdependencies between the most important cryptocurrencies' returns and volatilities, using the Diebold and Yilmaz (2009) approach. They suggest an emergent and time-varying interdependence between the cryptocurrencies analysed. More recent methodology is applied in Ji et al. (2019), specifically the Diebold and Yilmaz (2012, 2016) measures, 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. Leclair (2018) estimate market herding dynamics in the cryptocurrency market by adapting the CAPM framework as developed earlier by Huang and Salmon (2004). Thus, this methodology explores time variation in betas and cross-sectional dispersion of individual assets, showing a recent growing market herding.

Some other research includes Bação et al. (2018) who use 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. Symitsi and Chalvatzis (2018) examine 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. Charfeddine et al. (2020) use 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. In addition, cryptocurrencies may be suitable for financial diversification, but may form poor hedging instruments. Walther et al. (2019) applying the GARCH-MIDAS approach to forecast volatility of some relevant cryptocurrencies using different data frequencies. And propose different economic and financial drivers. They conclude that Global Real Economic Activity provides better volatility forecasts in bull and bear markets.

Beneki et al. (2019) use 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. Katsiampa et al. (2019a) apply pair-wise bivariate BEKK models to study interlinkages and conditional correlations between different pairs of cryptocurrencies. Specifically, they analyse 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. Katsiampa et al. (2019b) apply 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, Tu and Xue (2019) use 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.

Köchling et al. (2019) study, among other topics, the weak-form market efficiency in the cryptocurrency market analysing the measure "price delay" t\showing that it significantly decreases over time thereby supporting weak-form efficiency of the cryptocurrency market. Platanakis and Urquhart (2019) study Bitcoin, Litecoin, Ripple and Dash portfolio optimization and the correlation between them showing that the

Black–Litterman model with 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. Vidal-Tomas et al. (2019) study 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. Ahmed (2020) 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. Burnie (2018) 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. Papadimitriou et al. (2020) apply 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 behaviour of the cryptocurrency market. They conclude that there is strong evidence of a growing price synchronization in this market. Lebedeva (2018) 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. In addition, there are some cryptocurrencies that are less connected and less affected by shocks implying they are more attractive for investment purposes. Song et al. (2019) analyse 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

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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.

Adedokun (2019) use cointegrating tests and 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. Kyriazis (2019) provides a systematic survey of return and volatility spillovers of cryptocurrencies. Evidently, considering other cryptocurrencies and alternative assets. 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, Kyriazis (2019) detects volatility transmission among Bitcoin and national currencies. Gkillas et al. (2018) apply 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. Lo and Medda (2019) use panel ordinary least squares with cluster-robust standard errors to research the field of Tokenomics studying many blockchain tokens. This paper analyses 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, Canh et al. (2019) study 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 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 os that it enables us to simultaneously estimate both long-run and short-run asymmetries (Jareño et al., 2019a and 2020). In addition, for robustness, this study compares estimates from several frequency data (daily, weekly and monthly).

3. Data and Methodology

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 crypto-currencies 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 are provided by the coinmarket 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 March 7, 2020.

Our sample period runs from January 26, 2015 until March 7, 2020, which yields 1,868 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 March 8, 2020 and the recent stock market crash on March 9, 2020 caused by COVID-19.[1] These top ten cryptocurrencies in our sample did not come into existence all 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.

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[1] Due to this massive selloff, the cryptocurrency market lost $21 billion in market capitalization in twenty-four hours from Saturday March 7, 2020 to Sunday March 8, 2020 (from a total cryptocurrency market capitalization of $251.5 billion to $230.8 billion). Moreover, two weeks later, on March 22, 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 March 22, 2020.

[Please, insert Figure 1 about here]

[Please, insert Table 1 about here]

Figure 1 plots the evolution of the cryptocurrencies' daily prices and Table 1 also shows that two weeks later this massive selloff caused by COVID-19, the total cryptocurrency market capitalization has fallen by almost 40% from $251.5 billion to $167.1 billion. Consequently, the market capitalization of the top ten cryptocurrencies analysed in this paper has decreased by 36% for Bitcoin, 50% for Ethereum, 38.3% for Ripple, 42.2% for Bitcoin_cash, 0.065% for Tether, 34.7% for Bitcoin_sv, 43.9% for Litecoin, 45.7% for EOS, 48.5% for Binance_coin and 53.8% for Tezos. Thus, the cryptocurrency that has suffered the greatest percentage drop in its capitalization value is Tezos and, conversely, the cryptocurrency with the smallest percentage fall in its capitalization value is Tether (0.065%), which has positioned itself as the fourth crypto-currency in terms of market capitalization, ahead of Bitcoin_cash, since the latter did suffer a very high percentage loss (42.2%). As for the price of these top ten cryptocurrencies, these have decreased in the last two weeks by between 32% and 50%, except in the case of Tether, where this decrease is only 0.5%.

Figure 2 shows the time evolution of the Bitcoin returns and the rest of relevant cryptocurrencies returns. In addition, Table 2 collects the descriptive statistics and unit root tests of Bitcoin returns and returns of the rest of the top ten cryptocurrencies 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. In addition, the lower the frequency of data, the higher Bitcoin and the rest of altcoins' mean log-returns. The standard deviation indicates that the monthly log-returns are the most volatile data, so the lower frequency of data, the higher risk values measured through standard deviation. Most of cryptocurrency returns show positive skewness, except for Tezos returns for all three data frequencies. All variables show excess kurtosis, mainly 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 confirm that all cryptocurrency returns are stationary. However, for monthly data, it is interesting to note the limitation of the lack of data for some cryptocurrencies, which leads to doubts about the stationarity of Theter and Tezos returns.

[Please, insert Figure 2 about here]

[Please, insert Table 2 about here]

3.2. Methodology

To analyse the connectedness between Bitcoin returns and returns of the other top ten most relevant cryptocurrencies we use the NARDL (nonlinear autoregressive distributed lag) model developed by Shin et al. (2014). In detail, NARDL is applied to capture both long- and short-run asymmetries between our variables.

Thus, first, the asymmetric long-run regression of the top ten cryptocurrencies returns (Shin et al. 2014, Jareño et al., 2019a) is a simple approach to modelling asymmetric cointegration based on partial sum descompositions:

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

$$\Delta BR_t = v_t \quad [2]$$

where R_{jt} and BR_t are scalar I(1) variables. In detail, R_{jt} is the rest of the j-top ten cryptocurrencies returns corresponding to period t, BR_t is the Bitcoin returns to period t which is descomposed as $BR_t = BR_0 + BR_t^+ + BR_t^-$, where BR_t^+ and BR_t^- are partial sums processes 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.

$$\Delta BR_i^{+¿} = \sum_{i=1}^{t} max\left(\Delta BR_i, 0\right)$$
$$+¿ = \sum_{i=1}^{t} ¿ \quad [3]$$
$$BR_t^¿$$

$$\Delta BR_i^{-¿} = \sum_{i=1}^{t} min\left(\Delta BR_i, 0\right)$$
$$-¿ = \sum_{i=1}^{t} ¿ \quad [4]$$
$$BR_t^¿$$

Second, α^+ and α^-, in equation [1], capture the long-run relation between each of the top ten cryptocurrencies returns and increases (α^+) or decreases (α^-), respectively, in the

Bitcoin returns. Finally, we study whether the long-run relation would reflect asymmetric long-run Bitcoin returns passthrough to each of the top ten cryptocurrencies returns.

Moreover, in the framework of Shin et al. (2014), they affirm that the long-run relationship between R_{jt} and BR_t is modelled as piecewise linear subject to the descomposition 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 R_{jt} by a greater amount than a unit positive change would reduce it. So, Shin et al. (2014) confirm that the NARDL model includes a regime-switching cointegrating relationship in which regime transitions are governed by the sign of ΔBR_t.

Thus, Shin et al. (2014) developed the following flexible, dynamic, asymmetric and non-linear ARDL(p,q) model by extending the well-known linear autoregressive distributed lag (ARDL) bounds testing approach popularised by Pesaran and Shin (1998) and Pesaran et al. (2001):

$$
\begin{aligned}
& \gamma \\
& \dot{\iota} \\
& -\dot{\iota} \\
& +\dot{\iota}+\gamma_i^{-\dot{\iota}\,\Delta BR_{t-i}^{\dot{\iota}}}+\varepsilon_{jt}^{\Box} \\
& +\dot{\iota}\,\Delta BR_{t-i}^{\dot{\iota}} \\
& \dot{\iota} \\
& \dot{\iota} \\
& -\dot{\iota}+\sum_{i=1}^{p}\phi_i^{\Box} R_{t-i}^{\Box}+\sum_{i=0}^{q}\dot{\iota} \\
& +\dot{\iota}+\beta_3^{\Box}\cdot BR_t^{\dot{\iota}} \\
R_{jt}^{\Box} = & \beta_0^{\Box}+\beta_1^{\Box}\cdot R_{t-1}^{\Box}+\beta_2^{\Box}\cdot BR_t^{\dot{\iota}}
\end{aligned}
\qquad [5]
$$

where BR_t is a kx1 vector of multiple regressors defined such that $BR_t=BR_0+BR_t^++BR_t^-$, $\phi_i^{\Box}$ is the autoregressive parameter, p is the number of lagged dependent variables and q is the number of lags for regressors, $\gamma_i^{+\dot{\iota}}_{\dot{\iota}}$ and $\gamma_i^{-\dot{\iota}}_{\dot{\iota}}$ 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 respectively Bitcoin returns increases and decreases on each of the top ten

cryptocurrencies returns. On the other hand, $\sum_{i=0}^{q} \overset{\gamma_i^{+i}}{i}$ and $\sum_{i=0}^{q} \overset{\gamma_i^{-i}}{i}$ measures the short-run influences of increases and decreases (respectively) of Bitcoin returns on each of the top ten cryptocurrencies returns. Thus, not only the asymmetric long-run relation is considered, but the asymmetric short-run influences of Bitcoin returns changes on the top ten cryptocurrencies returns are also captured in order to identify relevant differences in the response of economic agents to positive and negative shocks.

Shin et al. (2014) affirm 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) improve the performance of the 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 nonlinear autoregressive distributed lag (NARDL) model of Shin et al. (2014) is really useful 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, Arize et al. (2017) and Jareño et al. (2019a and 2020) suggest some advantages of the NARDL methodology: (1) good small sample properties, (2) suitable regardless of the stationarity of the variables, (3) simultaneous estimates of short- and long-run coefficients, among others, (4) free of residual correlation and so, not prone to omitted lag bias.

On the other hand, empirical implementation of the NARDL approach involves to conduct classical unit root tests such as the standard Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test 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

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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. Concretely, 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

This section shows results of the non-linear ARDL estimation and collects long-run and short-run relations between Bitcoin returns and the rest of the top 10 cryptocurrencies returns for different frequencies (daily, weekly and monthly) for a sample period from 26 January 2015 to 7 March 2020.[2] In addition, it is noteworthy that the maximum lag order considered in these NARDL estimations is 4.

Thus, this fourth section consists of three sub-sections that show the results of NARDL models and the consequent asymmetry and cointegration tests between Bitcoin returns and the rest of the top ten cryptocurrencies returns for daily, weekly and monthly frequencies, respectively.

4.1. Results of the NARDL models: daily frequency

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2 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.

This sub-section shows the regression results of non-linear ARDL models and asymmetry and cointegration tests between Bitcoin returns and the rest of the top ten cryptocurrencies returns (Ethereum, XRP, Bitcoin Cash, Tether, Bitcoin SV, Litecoin, EOS, Binance coin and Tezos) for daily frequency in Table 3.

[Please, insert Table 3 about here]

Concretely, this table contains the Pearson's correlation coefficients, the Wald F test for the presence of cointegration, the cointegration equation (long-run elasticities) between Bitcoin returns and the rest of cryptocurrencies returns, the Wald test for long-run symmetry, the Wald test for short-run symmetry and the effect of the cumulative sum of positive and negative changes (respectively) in Bitcoin returns for (1-4)-lags on the rest of cryptocurrencies.

First, Table 3 shows, in its second column, the Pearson's correlation coefficients between Bitcoin returns and the rest of the top ten cryptocurrencies returns for daily frequency. This measure would be considered as a first approach to study the connectedness between them. The results show that the null hypothesis of no correlation (*H_0: PCorr=0*) is rejected by all the top ten cryptocurrencies. In concrete, a high positive correlation is observed between Bitcoin returns and all the rest of the top ten cryptocurrencies 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%.

Second, the Wald F test for the presence of cointegration is shown in the third column of Table 3. These results show that the null hypothesis of no cointegration that coefficients on the level variables are 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 bounds F-statistics show long-run relations, that is cointegration, between XRP, Bitcoin_cash, Tether, EOS and Binance_coin returns and changes in Bitcoin returns for daily frequency. Additionally, the long-run coefficients of changes in Bitcoin returns are positive and statistically significant at 1% significance level for these five cryptocurrencies, remarking the highest values of XRP and Theter.

Third, 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 retuns (*BR*) and the rest of the top ten cryptocurrencies' returns (R_{jt-i}). Thus, regarding the long-run elasticities for BR^+_{t-i} (the cumulative sum of positive changes in Bitcoin returns) and BR^-_{t-i} (the cumulative sum of negative changes in Bitcoin returns), all cryptocurrencies returns would respond in the same way to positive and negative changes in Bitcoin returns. In addition, the coefficients are quite similar for all cryptocurrencies and not very high. The largest coefficients correspond to Bitcoin_sv returns that response 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 EOS, XRP, Tether and Binance_coin at 1%, 5% and 5-10% (the last two cryptocurrencies) significance level, respectively. Moreover, the coefficients are negative for XRP and EOS, which move in the opposite direction to the changes in Bitcoin returns, but positive for Tether and Binance_coin, fluctuating in line with Bitcoin returns.

Fourth, the fifth column shows the Wald test for testing the long-run symmetry. These results show that the null hypothesis of long-run symmetry (*H₀:* $- \beta2/\beta1 = - \beta3/\beta1$), is just rejected 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.

Fifth, the sixth column shows the Wald test for testing the short-run symmetry. In this case, the null hypothesis of short-run symmetry (*H₀:* $\gamma_i^+ = \gamma_i^-$), is rejected by all the cryptocurrencies. In concrete, all cryptocurrencies show positive and statistically significant coefficients at 1% significance level. Therefore, there is strong evidence of asymmetric short-run responses of all cryptocurrencies returns to changes in Bitcoin returns for daily frequency. Thus, nonlinear asymmetries are relevant to study the short-run relationship between the top ten cryptocurrencies' returns and Bitcoin returns for daily data.

Sixth, 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 Jareño *et al.* (2019a and 2020), among others,

there would be a statistically significant effect of the cumulative sum of positive and negative changes in Bitcoin returns on most cryptocurrencies returns. Concretely, we observe a positive and statistically significant effect 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. On the other hand, we also notice just a 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). Therefore, we observe a 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 cryptocurrencies returns.

Finally, the explanatory power of the NARDL model, measured by the adjusted R^2, varies from a minimum of 14.5% (for Tether returns) 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 regression results of non-linear ARDL models and asymmetry and cointegration tests between Bitcoin returns and Ethereum, XRP, Bitcoin Cash, Tether, Bitcoin SV, Litecoin, EOS, Binance coin and Tezos returns for weekly frequency.

[Please, insert Table 4 about here]

Regarding the Pearson's correlation coefficients between Bitcoin returns and the rest of the top ten cryptocurrencies returns, shown in the second column of Table 4, we can affirm that the null hypothesis of no correlation is rejected by all the top ten cryptocurrencies. Concretely, there is a positive correlation between Bitcoin returns and all the rest of the top ten cryptocurrencies returns and all of them show statistical significance at the 1% level, reaching values higher that 40% in all cases. It is interesting to highlight the exception that Tether returns represent, showing a negative and statistically significant correlation with Bitcoin returns.

Next, the results of the Wald's F test for cointegration, listed in column three of Table 4, show that the null hypothesis of no cointegration is rejected by four cryptocurrencies

(Ethereum, Tether, EOS and Binance coin). Thus, the bounds F-statistics show long-run connectedness between Ethereum, Tether, EOS and Binance_coin returns and changes in Bitcoin returns for weekly frequency. Additionally, the long-run coefficients of changes in Bitcoin returns are positive in these four cryptocurrencies and significant at 5% significance level for Tether and EOS as well as significant at 10% significance level for Ethereum and Binance_coin.

The results of the cointegration equation between Bitcoin retuns and the returns of the rest of the top ten cryptocurrencies, collected in column four of Table 4, show that all cryptocurrencies returns (except for Litecoin returns) would respond in the same way to positive and negative changes in Bitcoin returns. In addition, 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. 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. Clearly, the Binance_coin returns response more to negative changes in Bitcoin returns because the coefficient is larger in this proof. In concrete, negative changes in Bitcoin returns show a six-fold increase in Binance_coin response than positive changes (11.9% versus 1.9%, respectively). Nevertheless, these elasticities are not statistically significant. Thus, the only long-run elasticities for the cumulative sum of positive and negative changes in Bitcoin returns are statistically significant just for XRP, EOS and Tether at 10%, 5% and 1% significance level, respectively. Moreover, the coefficients are negative for XRP and positive for EOS and Tether.

The results of the Wald test for testing the long-run symmetry, column five of Table 4, show that the null hypothesis of long-run symmetry is not rejected by any of the top ten cryptocurrencies. Thus, the Wald test indicates that there is symmetry in the long run impact of Bitcoin returns on all the rest of cryptocurrencies for weekly data.

The results of the Wald test for testing the short-run symmetry, column six of Table 4, show that the null hypothesis of short-run symmetry is rejected by all the cryptocurrencies. In concrete, all cryptocurrencies show positive and statistically significant coefficients at 1% significance level. Therefore, there is strong evidence of asymmetric short-run responses of all cryptocurrencies returns to changes in Bitcoin

returns for weekly frequency. So, nonlinear asymmetries are also relevant to study the short-run relationship between these cryptocurrencies for weekly data.

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, shown in columns seven and eight of Table 4, illustrates that, there would be a statistically significant short-run impact of increases slightly more than decreases of Bitcoin returns on most cryptocurrencies returns. In concrete, 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. On the other hand, 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. Weekly frequency data also corroborate a high persistence in the impact of both positive and negative changes in Bitcoin returns, for 1 to 4 lags, on half of the cryptocurrencies returns.

Finally, the explanatory power of the NARDL model measured by the adjusted R^2 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).

4.3. Results of the NARDL models: monthly frequency

Table 5 shows the regression results of non-linear ARDL models and asymmetry and cointegration tests between Bitcoin returns and Ethereum, XRP, Bitcoin Cash, Tether, Bitcoin SV, Litecoin, EOS, Binance coin and Tezos returns for monthly frequency. It should be noted that monthly data may give inaccurate results because some cryptocurrencies are very recent and provide little monthly data for this study. 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 analyse the monthly results taking into account this weakness and limitation.

[Please, insert Table 5 about here]

The results of Pearson's correlation between Bitcoin returns and the rest of the top ten cryptocurrencies' returns are collected in column two of Table 5. We can affirm that the null hypothesis of no correlation is rejected by just six out of nine cryptocurrencies. In concrete, a positive and statistically significant relation is observed between Bitcoin returns and Ethereum, Bitcoin_cash, XRP, Litecoin, EOS and Binance_coin returns at 1%, 5% and mainly, 10% significance level. It is interesting to note that the three cryptocurrencies that do not reject the null hypothesis are precisely the two most recent and Tether, 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, collected 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 XRP, Tether, Bitcoin_sv, Litecoin, EOS and Tezos returns and changes in Bitcoin returns for monthly frequency. In addition, the long-run coefficients of changes in Bitcoin returns are positive and statistically significant in these six cryptocurrencies. Anyway, we have to take into account that the magnitude of the F-statistic in the case of Tezos is five times greater than in the rest of cryptocurrencies and even more in the case of Bitcoin_sv where its F-statistic is nine times greater than in the rest of cryptocurrencies. The result of these two cryptocurrencies is most likely because they are the two most recent and provide little monthly data for this analysis.

The results of the cointegration equation between Bitcoin retuns and the returns of the rest of the top ten cryptocurrencies, listed in column four of Table 5, show that all cryptocurrencies returns would respond in the same way to positive and negative changes in Bitcoin returns. In addition, the coefficients are quite similar for most cryptocurrencies except for the two most current ones: the second most recent, Tezos, where the coefficient of negative changes in Bitcoin returns is twice as high as the coefficient of positive changes and especially the most recent, Bitcoin_sv, where the coefficient of negative changes is almost nine times higher than the coefficient of positive changes (61% *vs.* 7.2%, respectively). 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 at 5%, 5-1% and 1% significance level, respectively and, additionally, just the coefficient of negative changes in Bitcoin returns for Bitcoin_sv (the most recent cryptocurrency) and EOS at 5% significance level.

The results of the Wald test for testing the long-run symmetry, column five of Table 5, show that the null hypothesis of long-run symmetry is just rejected by Bitcoin_sv and Tezos and it could indicate that there could be asymmetry in the long run impact of Bitcoin returns at these two most recent cryptocurrencies with very few monthly data, as previously observed with the analysis of the cointegration equation.

The results of the Wald test for testing the short-run symmetry, column six of Table 5, show that all cryptocurrencies reject the null hypothesis of short-run symmetry because all of them show positive and statistically significant coefficients at 1% significance level, except for Tether and Bitcoin_sv that show negative and statistically significant coefficients at 5% and 1% significance level, respectively. Therefore, all cryptocurrencies 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 cryptocurrencies returns is shown in columns seven and eight of Table 5. Concretely, there is a positive and statistically significant effect of the cumulative sum of positive changes in Bitcoin returns on seven out of nine cryptocurrencies 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. On the other hand, there is also 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 cryptocurrencies 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. Consistently, 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 cryptocurrencies returns.

Moreover, the explanatory power of the NARDL model varies from a minimum adjusted R^2 of 26.8% (for Tether returns) to a maximum of 96.6% (for Bitcoin_sv returns), taking into account the limitation of the lack of data for the analysis with monthly frequency.

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 relevant cryptocurrencies that is Ethereum, XRP, Bitcoin Cash, Tether, Bitcoin SV, Litecoin, EOS, Binance coin and Tezos applying a non-linear autoregressive distributed lag (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 rest of relevant cryptocurrencies selected in terms of recent market capitalization, by using the NARDL approach to evaluate both long- and short-run asymmetries.

As we have seen throughout this section, the Pearson's correlation coefficients 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, because the lack of data.

Additionally, the Wald F-test for the presence of cointegration indicates that there is cointegration or long-run relation between most cryptocurrencies returns and changes in Bitcoin returns for all frequencies.

Moreover, the cointegration equation that shows the long-run elasticities between Bitcoin returns and the rest of cryptocurrencies reveals that cryptocurrencies returns would usually respond in the same way to positive and negative changes in Bitcoin returns, with very few exceptions.

Furthermore, the Wald test indicates that there could be asymmetry in the long-run impact of Bitcoin returns just in a maximum of two out of nine cryptocurrencies returns but there is strong evidence of asymmetry in the short-run impact of Bitcoin returns in all cryptocurrencies returns for all frequencies. This evidences that nonlinear

asymmetries are especially needed to analyse the short-run relations between these cryptocurrencies.

In general, there is a positive as well as a negative and statistically significant effect of the cumulative sum of positive and negative changes in Bitcoin returns on most cryptocurrencies returns for daily, weekly and monthly frequencies. This evidence corroborates a high persistence in the impact of both positive and negative changes in Bitcoin returns, for 1 to 4 lags, on most of the cryptocurrencies returns.

The explanatory power of the NARLD models is relevant for all frequencies. Thus, leaving aside the monthly frequency, due to the lack of data, both daily and weekly frequencies manage to explain more than 40% and 50%, respectively, of the cryptocurrencies returns with changes in Bitcoin returns.

Our results would have relevant implications for market participants, because potential connectedness between the top cryptocurrencies' returns may affect the decision-making of investors and policy-makers. Thus, future research lines could be to extend our study to the analysis of potential co-movements in volatility in the cryptocurrency market, that have a key role for implementing suitable investment strategies as well. To perform more informed decisions, an extensive study of interdependencies between cryptocurrencies and conventional assets would be 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 crypt-currency market, especially in periods of economic recession.

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Table 1. Top 10 Cryptocurrencies by Market Capitalization (Date: March 7, 2020/ March 22, 2020)(Total market capitalization: $251,5 billion/ $167,1 billion)

Name	Market Cap	Price	Volume (24h)	Circulating Supply	Change (24h)	Starting date
Bitcoin	$166,743,993,933 $106,591,196,069	$8,887.80 $5,830.25	$47,868,579,352 $40,099,664,740	18,238,800 BTC 18,282,425BTC	-0.21% -5.73%	01/26/2015
Ethereum	$26,966,016,878 $13,590,860,527	$237.32 $123.32	$25,206,666,119 $12,497,707,224	109,863,231 ETH 110,207,055 ETH	2.07% -7.05%	03/10/2016
XRP	$10,688,702,708 $6,585,765,149	$0.23624 $0.150214	$3,252,412,868 $1,864,979,798	43,749,413,421 XRP* 43,842,625,397 XRP*	-0.88% -5.02%	01/26/2015
Bitcoin Cash	$6,364,459,307 $3,736,418,941 (5º)	$330.77 $203.67	$6,617,099,625 $4,015,953,536	18,300,000 BCH 18,345,250 BCH	-0.25% -7.47%	08/03/2017
Tether	$4,641,437,047 $4,637,871,717 (4º)	$1.0047 $0.99903	$66,519,050,406 $49,036,623,749	4,642,367,414 USDT* 4,642,367,414 USDT*	0.16% -0.21%	04/15/2017
Bitcoin SV	$4,439,960,724 $2,894,145,363	$233.95 $157.78	$3,344,789,290 $3,365,019,330	18,297,290 BSV 18,342,440 BSV	-1.66% -6.35%	11/19/2018
Litecoin	$4,072,866,599 $2,292,391,578	$60.45 $35.63	$6,342,837,357 $3,148,219,029	64,168,987 LTC 64,342,318 LTC	-0.77% -7.34%	08/24/2016
EOS	$3,526,893,934 $1,965,191,547	$3.64 $2.13	$6,064,573,978 $2,921,411,201	920,452,308 EOS* 921,045,767 EOS*	-0.47% -6.45%	07/02/2017
Binance Coin	$3.292,877,236 $1,735,514,181	$20.24 $11.16	$427,799,971 $308,670,064	155,536,713 BNB* 155,536,713 BNB*	-1.68% -7.48%	11/09/2017
Tezos	$2,250,710,445 $1,038,511,561	$2.98 $1.47	$317,321,520 $113,589,399	702,028,555 XTZ* 704,565,511 XTZ*	-0.04% -11.11%	02/02/2018

Source: Coinmarketcap website

Table 2. Descriptive statistics of Bitcoin returns and returns of the rest of the top ten cryptocurrencies returns

Panel A: Daily frequency

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	JB stat.	ADF stat.	PP stat.	KPSS stat.
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

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	JB stat.	ADF stat.	PP stat.	KPSS stat.
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

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	JB stat.	ADF stat.	PP stat.	KPSS stat.
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

Notes: 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.

Table 3. Regression results of non-linear ARDL models: asymmetry and cointegration tests between Bitcoin returns and the rest of relevant cryptocurrencies' returns: daily frequency

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

Notes: 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 cryptocurrencies returns.

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

Table 4. Regression results of non-linear ARDL models: asymmetry and cointegration tests between Bitcoin returns and the rest of relevant cryptocurrencies' returns: weekly frequency

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

Notes: 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 $R_{tt-i} = e^+ \cdot BR^+_{t-i} + e^- \cdot BR^-_{t-i}$. **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 cryptocurrencies returns.

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

Table 5. Regression results of non-linear ARDL models: asymmetry and cointegration tests between Bitcoin returns and the rest of relevant cryptocurrencies' returns: monthly frequency

Cryptocurrencies	PCorr	Coint	Eq	LAsym	SAsym	Lags $^+$	Lags $^-$	Adj. R^2
Ethereum	0.6352 ***	0.1902	e^+: -0.8061 e^-: -1.0821	0.0205	3.9753 ***	--	--	0.4302
XRP	0.4454 *	4.4249 ***	e^+: 0.1575 e^-: 0.4109	0.9089	2.7308 ***	--	--	0.2721
Bitcoin_cash	0.5927 **	0.4673	e^+: 0.7670 e^-: 0.4763	0.1481	4.8457 ***	(1): 1.1441 ***	--	0.5652
Tether	-0.1473	3.8636 **	e^+: 0.0203 ** e^-: 0.0289 **	1.8779	-2.5775 **	(1): 0.0210 **	(1): -0.0292 *	0.2680
Bitcoin_sv	0.2854	34.743 ***	e^+: 0.7260 e^-: 6.0939 *	46.084 ***	-3.2676 ***	(1): 2.8139 * (2): 2.4948 *	--	0.9657
Litecoin	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	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	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	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

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

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)
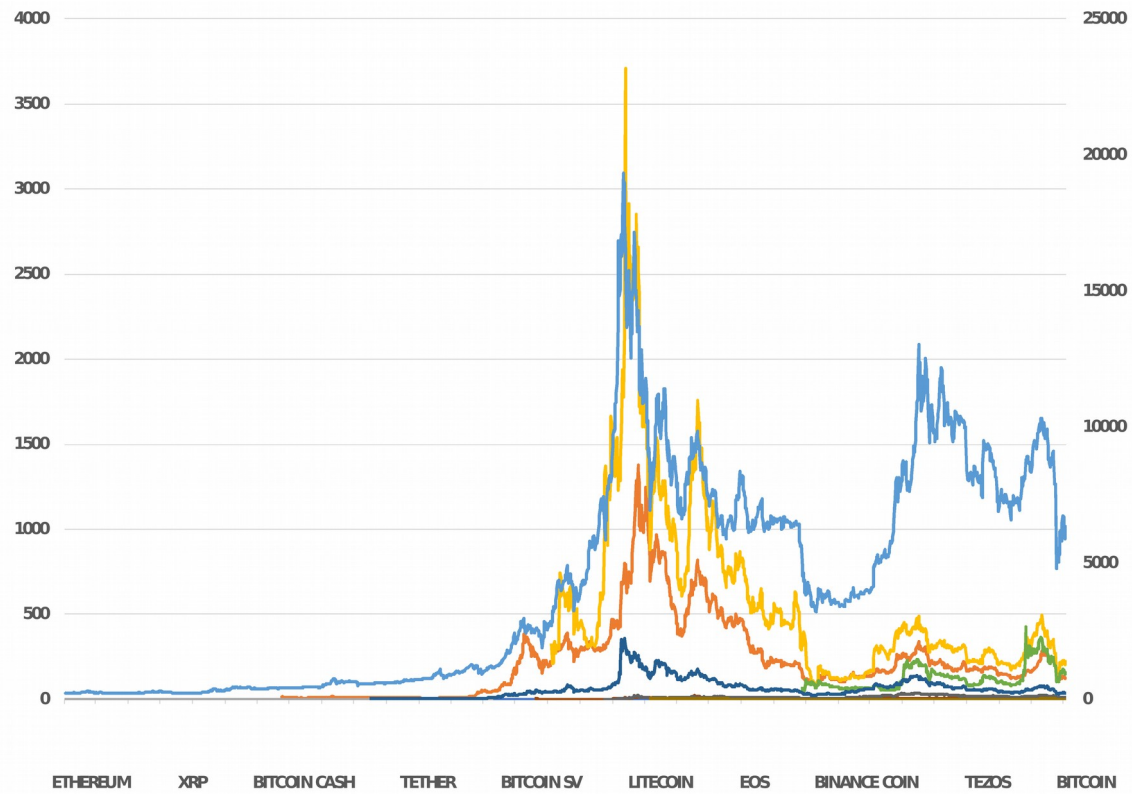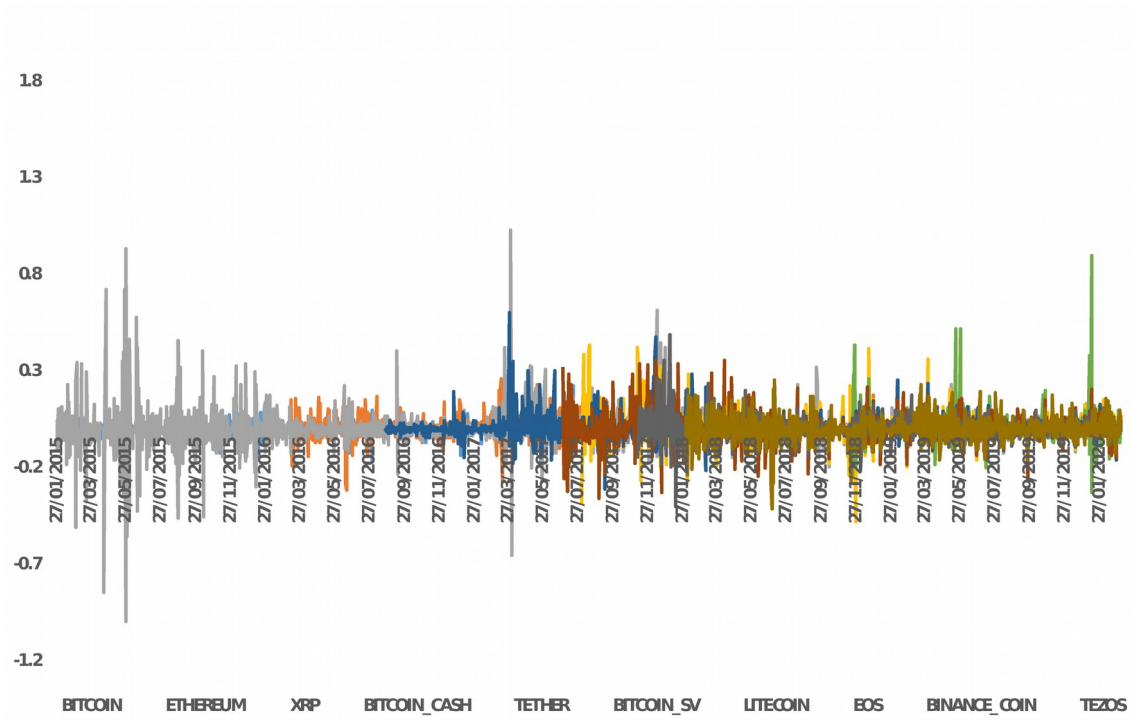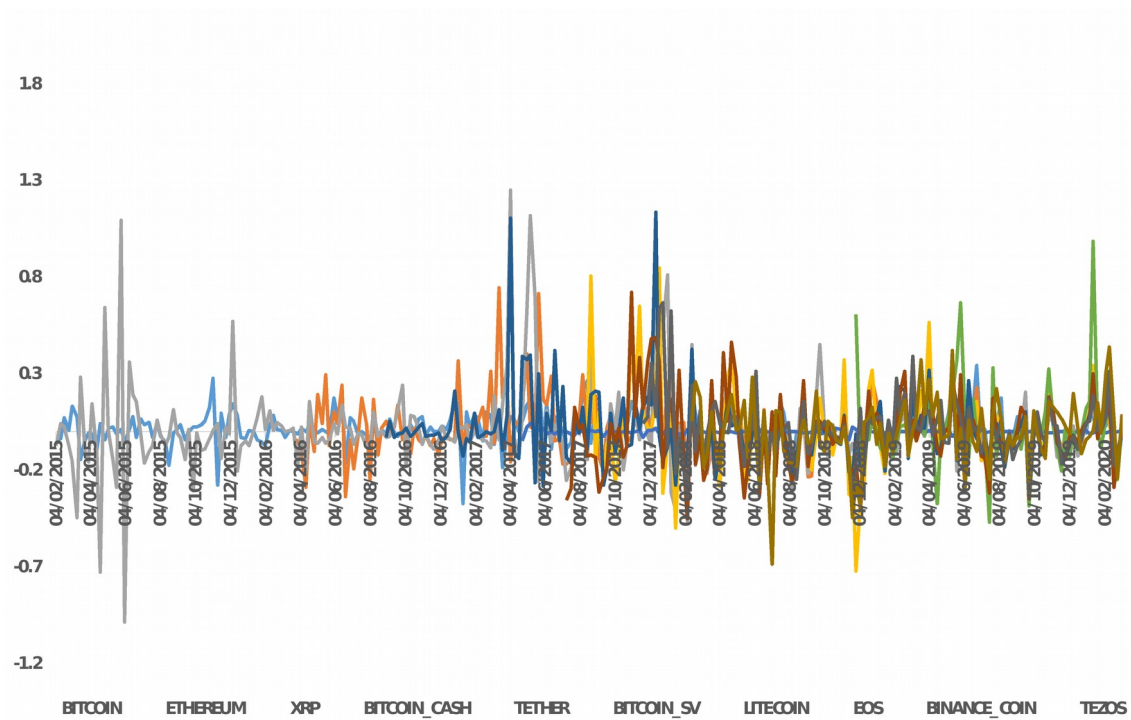
Figure 2. Time evolution of the Bitcoin returns and the rest of relevant cryptocurrencies returns

Panel A: Daily frequency

Panel B: Weekly frequency

Panel C: Monthly frequency