



Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

The asymmetric effect of bitcoin on altcoins: evidence from the nonlinear autoregressive distributed lag (NARDL) model

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ARTICLE INFO

Keywords:

Bitcoin
Cryptocurrency
Asymmetry
Ethereum
Ripple
Litecoin
NARDL

JEL Classification:

C32
G15
E42
G12
C12

ABSTRACT

This paper examines the asymmetric effect of Bitcoin on three altcoins, namely Ethereum (ETH), Ripple (XRP) and Litecoin (LTC) by using the Nonlinear Autoregressive Distributed Lag (NARDL) model for the period July 2015 to March 2019. We provide evidence on the asymmetric impact of Bitcoin on altcoins both in the short-run and in the long-run. In the short-run, a decrease in Bitcoin price has greater effect than an increase on the prices of altcoins. This asymmetry is more frequent after the 2017 cryptocurrency price crash.

1. Introduction

Bitcoin was introduced by Nakamoto (2008) as a digital currency and open-source online payment system. Especially with its highly volatile price and future prospect, it attracts the attention of investors, regulatory bodies, and media. Following Bitcoin, around 2,000 cryptocurrencies have been released and most of them are traded in international markets (Ballis and Drakos, 2020). However, Bitcoin has a dominant role in the market with a share around 65% in market capitalization by May, 2020.

The literature on financial aspects of the cryptocurrency market has recently emerged and is developing rapidly. For instance, several studies explore the relationship between investors' attention and Bitcoin prices (Urquhart, 2018; Dastgir et al., 2019; Kraaijeveld and De Smedt, 2020), the existence of bubbles in the cryptocurrency market (Cheah and Fry, 2015; Corbet et al., 2018a),

Funding: This research has been financed by Spanish Public Funds through Ministry of Economy and Competitiveness in the framework of the project ECO2017-84864-P.

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<https://doi.org/10.1016/j.frl.2020.101754>

Received 23 September 2019; Received in revised form 4 August 2020; Accepted 3 September 2020
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the efficiency of cryptocurrencies (Urquhart, 2016; Sensoy, 2019), and hedging capabilities of cryptocurrencies (Bouri et al., 2017; Poyser, 2019; Demir et al., 2018; Gozgor et al., 2019; Walther et al., 2019; Demir et al., 2020).

Another strand of this literature examines the interrelationship between Bitcoin and other cryptocurrencies. By using Autoregressive Distributed Lag Model, Ciaian et al. (2018) show that Bitcoin and altcoin markets are interdependent, being such relationship significantly stronger in the short-run than in the long-run. 15 out of 16 altcoins are affected from shocks to Bitcoin in the short-run, while only four altcoins are cointegrated with Bitcoin prices in the long-run. Corbet et al. (2018b) find that Bitcoin prices affect Ripple and Litecoin while these cryptocurrencies have limited effect on Bitcoin, given that Bitcoin is the clear leader in the cryptocurrency market. In terms of volatility spillovers, Bitcoin has less effect on other cryptocurrencies while Litecoin's volatility shocks have significant effects on Bitcoin and Ripple. Ji et al. (2019) emphasize the important role of Bitcoin and Litecoin as they take place in the center of the return and volatility connectedness networks. This implies that volatility and return shocks of Bitcoin and Litecoin have significant effects on other cryptocurrencies. According to Katsiampa (2019a), there are interdependencies between Ether and Bitcoin and conditional volatility and correlation of those two cryptocurrencies are sensitive to major news. In a similar vein, Sifat et al. (2019) show that there is a bi-directional causality between Bitcoin and Ethereum by using hourly and daily data. By using data for five major cryptocurrencies, Katsiampa (2019b) shows that there are significant interdependencies. For Bitcoin, Ether, Ripple, and Litecoin (except Stellar Lumen), conditional volatility can capture asymmetric effects between good and bad news. Katsiampa et al. (2019a) document a bi-directional shock transmission between Bitcoin and both Litecoin and Ether. On the other hand, according to Zięba et al. (2019), Bitcoin prices do not affect and are not affected from other cryptocurrencies while there are interdependencies between cryptocurrencies except Bitcoin. On the contrary, Yaya et al. (2019) show that there are cointegration relationships between Bitcoin and altcoins which weakens in the post-crash period. Yi et al. (2018) mention that volatility connectedness among eight cryptocurrencies changes in time and rises when there is uncertainty. A further analysis of 52 cryptocurrencies show that they are interconnected and cryptocurrencies with higher market caps are more likely to generate volatility shocks to others. Antonakakis et al. (2019) document that there is large dynamic variability in the total connectedness of cryptocurrencies. Low market uncertainty leads to a weaker connectedness while during high market uncertainty, connectedness become stronger. Bitcoin behaves as a net transmitter of spillovers to other cryptocurrencies. Katsiampa et al. (2019b) examine conditional volatility dynamics and co-movements of eight cryptocurrencies. They show that there are strong interdependencies between cryptocurrencies.

Previous literature provides mixed results on the relationship between Bitcoin and other cryptocurrencies. This paper examines the asymmetric effects of Bitcoin (BTC) on altcoins, namely Ethereum (ETH), Ripple (XRP) and Litecoin (LTC), by using the Non-linear Autoregressive Distributed Lag (NARDL) approach. Bitcoin is expected to affect altcoins, as Bitcoin is the dominant cryptocurrency in terms of market capitalization and public interest. Compared to other cryptocurrencies, Bitcoin is more likely to serve as the preferred medium of exchange due to its usage for a wider range of goods and services. Likewise, Bitcoin is preferred for investment purposes. Moreover, for initial coin offerings (ICO) and altcoin sales transactions, investors are likely to use Bitcoin (Ciaian et al. 2018). To our knowledge, this is the first paper presenting evidence on the asymmetric effects of Bitcoin to altcoins. We provide evidence on the asymmetric impact of Bitcoin on altcoins both in the short-run and in the long-run. In the short-run, a decrease in Bitcoin price has greater impact than an increase on the price of altcoins. The asymmetry is more frequent after the December 2017 cryptocurrency price crash.

The rest of the paper is structured as follows. Section 2 presents the data and methodology. Findings are given in Section 3 and last section concludes the paper.

2. Empirical design

2.1. Data

Daily price data are used for Bitcoin and top three altcoins, namely Ethereum (ETH), Ripple (XRP) and Litecoin (LTC)¹, which have been obtained from www.coinmarketcap.com. We follow the model of Ciaian et al. (2018) and introduce several control variables to the estimations. Wikipedia visits for each altcoin per day² are included to control for the virtual media attention-driven demand. Oil price, gold price, 10-year treasury maturity rate, USD/EUR parity, and Nasdaq Composite Index are also comprised in the model to account for global macroeconomic and financial developments. The data period used is July 2015 – March 2019³. Table 1 presents the descriptive statistics of the variables.

2.2. Methodology

The literature uses the Non-linear Autoregressive Distributed Lag (NARDL) approach to examine the asymmetric effects of exchange rates to exports (Verheyen, 2013), uncertainty to gold prices (Bilgin et al. 2018), exchange rates to investments (Bahmani-Oskooee et al., 2018) and uncertainty to money demand (Bahmani-Oskooee and Nayeri, 2018). In terms of cryptocurrencies, Bouri et al. (2018) examine the asymmetric relationship between Bitcoin, stock price, gold price, bond price, commodity prices, and

¹ Those altcoins are listed in top three after Bitcoin at www.coinmarketcap.com

² obtained from <https://tools.wmflabs.org/pageviews>

³ Starting period of the data is related with the data availability of Wikipedia visits.

Table 1.
Descriptive statistics.

Variables	Mean	Max.	Min.	Std. Dev	Skewness	Kurtosis	Jarque-Bera
Panel A: Cryptocurrencies							
Bitcoin (BTC)	7.507748	9.858187	5.349438	1.265053	-0.0285	1.550517	78.64633
Ripple (XRP)	-2.85199	1.163151	-5.49921	2.068892	0.012248	1.240003	115.7949
Ethereum (ETH)	3.853932	7.16992	-0.8328	2.192747	-0.4175	1.960519	66.44287
Litecoin (LTC)	2.853423	5.881482	0.966984	1.521205	0.159462	1.430842	95.82837
Panel B: Macro-Financial Variables							
Gold	9.428241	9.522374	9.258559	0.058924	-0.89438	3.239685	121.7348
Nasdaq Composite	8.702517	9.000815	8.358629	0.178125	-0.01995	1.608219	72.45692
10yr Treasury Rate	0.837395	1.175573	0.314811	0.199525	-0.44132	2.412675	42.00902
USD/EUR	0.12611	0.222183	0.036814	0.041326	0.200566	2.554108	13.4448
Oil price	3.988221	4.455161	3.258481	0.233548	-0.24624	2.735287	11.68361
Panel C: Virtual media attention driven demand							
Search_XRP	6.696613	10.53356	4.919981	1.058582	0.836276	3.393315	110.3358
Search_ETH	7.790356	10.32529	5.953243	0.848732	0.417859	2.771897	28.04831
Search_LTC	6.367725	10.69673	5.010635	1.036713	0.989615	3.266677	149.0691

US dollar index. The NARDL approach is useful to study asymmetric impact in the long-run and in the short-run by modeling asymmetric cointegration. Moreover, the joint analysis of nonlinearity and non-stationarity can be done through an unrestricted error correction model. In this regard, Bitcoin return series is decomposed into partial sum of positive (negative) decompositions as it is suggested by [Shin et al. \(2014\)](#) as the following:

$$BTC_t^+ = \sum_{j=1}^t \Delta BTC_t^+ = \sum_{j=1}^t \max(\Delta BTC_t, 0), \quad BTC_t^- = \sum_{j=1}^t \Delta BTC_t^- = \sum_{j=1}^t \min(\Delta BTC_t, 0) \quad (1)$$

where BTC denotes Bitcoin prices. The asymmetric error correction model (AECM) is as follows:

$$\begin{aligned} \Delta ALT_t = & \alpha + \alpha_1 ALT_{t-1} + \beta_1 BTC_{t-1}^+ + \beta_2 BTC_{t-1}^- + \beta_3 GOLD_{t-1} + \beta_4 NASDAQ_{t-1} + \beta_5 OIL_{t-1} + \\ & \beta_6 TENYR_{t-1} + \beta_7 WIKI_{t-1} + \sum_{i=0}^j \gamma_1 \Delta GOLD_{t-i} + \sum_{i=0}^k \gamma_2 \Delta NASDAQ_{t-i} + \sum_{i=0}^m \gamma_3 \Delta OIL_{t-i} + \\ & \sum_{i=0}^n \gamma_4 \Delta TENYR_{t-i} + \sum_{i=0}^p \gamma_5 \Delta WIKI_{t-i} + \sum_{i=1}^r \gamma_6 \Delta ALT_{t-i} + \sum_{i=0}^z (\delta_i^+ \Delta BTC_{t-i}^+ + \delta_i^- \Delta BTC_{t-i}^-) + \mu_t \end{aligned} \quad (2)$$

where ALT stands for altcoin prices, GOLD for gold prices, NASDAQ for Nasdaq Composite Index, OIL for oil prices, TENYR for 10-yr treasury maturity rate and WIKI for daily Wikipedia search number for each cryptocurrency. All variables are in daily logarithmic level series following [Bouri et al. \(2018\)](#).

If $\delta_i^+ = \delta_i^-$ for all $i=0, \dots, z$ then it can be said that the effect is symmetric in the short-run. By following the same logic, if $\beta_1 = \beta_2$ then we cannot reject symmetry condition in the long-run. In order to observe cointegration, we use NARDL bounds test approach, which is developed by [Shin et al. \(2014\)](#). The main advantage of this approach is that, it is applicable even if the variables are $I(0)$, $I(1)$ or mutually cointegrated. Moreover, the series need not to be integrated in the same order to find a cointegrating relationship. The only limitation is, the variables should be integrated at most of order one.

By performing Augmented Dickey Fuller tests, we check whether all our variables are eligible to be present in our model. The test results indicate that except daily Wikipedia visits, which is $I(1)$, all explanatory variables in our model are $I(0)$.⁴ Therefore, the specification for NARDL approach is met. In this methodology, we use BDM t-statistic (t_{BDM}) ([Banerjee et al., 1998](#)) and PSS F-statistic (FPSS) test (Pesaran et al, 2001) to detect cointegration. In this regard, the null hypothesis (no cointegration) against the alternative hypothesis (cointegration) is tested. The hypotheses for the FPSS can be shown as,

$$H_0: \alpha_1 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$$

against the alternative that H_0 is not true. There are two critical values for these tests. If the value obtained from the test result is greater than the upper bound, we can conclude that there is cointegration. On the contrary, if the test statistic is less than the lower bound or it falls between the boundaries, then there is no evidence of a long-run relationship.

[Yaya et al. \(2019\)](#) show that the strength of relationships between Bitcoin and altcoins change after the market crash in December 2017. In order to capture the effect of cryptocurrency price crash on asymmetric relationship, we divide the sample into two as pre-crash (before December 2017) and post-crash (after December 2017) periods as it is suggested by [Yaya et al. \(2019\)](#).

3. Findings

Results of the bounds cointegration test are reported in [Table 2](#). The results obtained from F_{PSS} and T_{BDM} tests verify that there exists a long-run relationship between altcoin price and their explanatory variables for all altcoins. After fulfilling the cointegration

⁴ We did not report the results to save space, but they can be provided upon request.

Table 2
Bounds cointegration test.

Altcoins	Time Period	t_{BDM}	F_{PSS}
Ethereum	Pre-Crash	-4.83**	8.03***
	Post-Crash	-3.60	4.06***
	Full Sample	-4.72**	7.60***
Ripple	Pre-Crash	-3.26	5.48***
	Post-Crash	-5.44***	10.14***
	Full Sample	-6.08***	14.80***
Litecoin	Pre-Crash	-4.82**	7.89***
	Post-Crash	-4.19*	8.93***
	Full Sample	-4.95**	9.96***

Note: * indicate significance at 10% level, ** indicate significance at 5% level, *** indicate significance at 1% level. For t_{BDM} test the critical values are -2.57 and -4.04, -2.86 and -4.38, -3.43 and -4.99 for 10%, 5% and 1%, respectively. For F_{PSS} the critical values are 1.99 and 2.94, 2.27, and 3.28, 2.88 and 3.99 for 10%, 5%, and 1%, respectively.

specification, we continue with the estimated short-run and long-run coefficients which are presented in Table 3. In our analysis, we use AIC (Akaike Information Criteria) to determine optimal lag length.

We begin our analysis with full sample results. In all established models, it can be observed that Bitcoin has a statistically significant and positive effect in the short-run. Meaning that, an increase in Bitcoin price drives all three altcoins' prices up and vice versa. However, it is also shown that increases and decreases in the Bitcoin price have different effects on altcoins. In order to test the presence of an asymmetric effect of Bitcoin on altcoins in the short-run, we follow "additive short-run symmetry condition" which is proposed by Shin et al. (2009). This proposition states that the symmetry condition can only be rejected if the sum of decreases are significantly different from the sum of increases. Consequently, we construct our Wald-test based on this proposition and reject the null hypothesis at 5% and conclude that the impact of a decrease in Bitcoin price on altcoins is greater than the impact of an increase. This implies that altcoins are more sensitive to decreases than to increases in Bitcoin prices.

For the case of long-run, we only observe asymmetry for the case of Ripple. The coefficient of Bitcoin is negative and the impact of a decrease is again higher than the impact of an increase. For Litecoin and Ethereum, Bitcoin price is not significant and consequently we do not observe any asymmetry.

We also examine whether great crash in cryptocurrency market (Yaya et al., 2019) occurred in December 2017 changes the structure of relationship between Bitcoin and altcoins. The findings indicate that the asymmetric behavior is more frequent in post-crash period. We do observe asymmetric effect of Bitcoin price on all altcoins in post-crash period. For the case of short-run, the asymmetric pattern that is observed for full sample applies. The impact of a decrease in Bitcoin price dominates the case for an increase for all altcoins. Taking long-run results into consideration, we only observe an asymmetry in Litecoin equation. Unlike previous cases, here, the impact of an increase in Bitcoin dominates the one for a decrease. For Ethereum and Ripple, the symmetry condition cannot be rejected based on Wald-test. For post-crash period, it is also worthy to note that Bitcoin has a positive coefficient for all altcoins in the long-run, being different from the observation that we have for full sample in Ripple. When pre-crash period is taken into account, it can be said that the only asymmetry is in Litecoin equation. Both for the long-run and the-short run, the negative effect of Bitcoin is greater for the case of Litecoin.

Through nine models that we establish, seven of them indicate an asymmetric impact of Bitcoin on altcoins in the short-run, while it is just three for the long-run. According to this result, it can be said that the asymmetric behavior of Bitcoin on altcoins is mainly concentrated in the short-run. Apart from that, the negative impact of Bitcoin surpasses the positive one almost in all cases. On this basis, we imply that the negative effect of Bitcoin dominating the positive effect is more frequent. Lastly, we indicate that the asymmetry is more frequent in the post-crash period in the short-run. This finding is in line with the current literature, as Yaya et al. (2019) also observe a change in the dynamics between Bitcoin and altcoins in terms of volatility and shock persistence when pre-crash and post-crash periods are compared.

4. Conclusion

This paper examines the asymmetric impact of Bitcoin on altcoins. By using a Non-linear Autoregressive Distributed Lag (NARDL) approach, our findings suggest that Bitcoin price affects prices of altcoins asymmetrically in the short-run for all altcoins. Specifically, a decrease in Bitcoin price has a greater impact on altcoins compared to an increase. This finding provides an insight for the investors in altcoins. As we previously discussed, Bitcoin is the main cryptocurrency and the leader of the market. In this regard, the investors of altcoins should consider to re-design their portfolios as we provide evidence of a non-linear relationship between Bitcoin and altcoins. We also analyze the impact of the December 2017 great crash on the asymmetric behavior and show that the main source of asymmetry in full sample is originated from the post-crash period in the short-run. Further research can examine the asymmetric effect in bull and bear market periods.

Table 3

	Ethereum			Litecoin			Ripple			Full-Sample		
	Pre-Crash	Post-Crash	Full-Sample	Pre-Crash	Post-Crash	Full-Sample	Pre-Crash	Post-Crash	Full-Sample	Pre-Crash	Post-Crash	Full-Sample
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
$\Delta LTC_t - 1$	-0.06***	0.011	-0.05***	0.013	-0.03***	0.007	-0.04***	0.008	-0.06***	0.019	-0.03***	0.006
ΔBTC_t^+	0.43***	0.135	0.46***	0.118	0.41**	0.092	0.33***	0.094	0.67***	0.111	0.44***	0.088
ΔBTC_t^-	0.67***	0.145	1.16***	0.092	0.94***	0.102	1.18***	0.099	1.06***	0.101	1.14***	0.089
$\Delta BTC_t - 1^+$												
$\Delta BTC_t - 1^-$			-0.17*	0.091	-0.18**	0.009						
$\Delta BTC_t - 2^+$												
$\Delta BTC_t - 2^-$												
$\Delta BTC_t - 3^+$												
$\Delta BTC_t - 3^-$												
$BTC_{t-1}^+ - 1$	0.01	0.023	0.11***	0.026	0.03	0.010	-0.03*	0.019	0.11***	0.036	0.01	0.008
BTC_{t-1}^-	-0.01	0.035	0.11***	0.027	0.02	0.011	-0.06**	0.027	0.08**	0.034	-0.01	0.009
R ²	0.225		0.531		0.238		0.342		0.501		0.380	
χ^2_{HET}	3.252	[0.000]	6.511	[0.000]	8.152	[0.000]	4.652	[0.000]	5.212	[0.000]	7.593	[0.000]
χ^2_{SER}	1.121	[0.335]	1.611	[0.125]	0.916	[0.416]	0.012	[0.912]	0.384	[0.511]	0.309	[0.577]
χ^2_{WR}	1.108	[0.292]	8.483	[0.003]	4.267	[0.039]	30.16	[0.000]	4.852	[0.028]	36.73	[0.000]
W_{LR}	2.331	[0.127]	0.007	[0.932]	0.965	[0.326]	3.567	[0.059]	5.583	[0.018]	0.235	[0.627]

Note: The superscript "+" and "-" denote positive and negative cumulative sums, respectively. χ^2_{HET} and χ^2_{SER} denote heteroskedasticity test and LM test for serial correlation, respectively. Empty cells indicate the variable is either insignificant or not present in the model. Heteroskedasticity consistent standard errors are used. Value in [] are p-values. S.E. stands for standard errors. ** indicate significance at 10% level. * indicate significance at 5% level. *** indicate significance at 1% level. w_{SR} and w_{LR} stand for short-run and long-run Wald-test, respectively. The coefficient of ALT is the error correction term for every altcoin equation. Virtual media attention-driven demand and global macroeconomic/financial variables are included in all estimations however; we did not report the coefficients to save space.

CRediT authorship contribution statement

Ender Demir: Conceptualization, Methodology, Writing - review & editing. **Serdar Simonyan:** Data curation, Methodology, Formal analysis, Writing - review & editing. **Conrado-Diego García-Gómez:** Conceptualization, Writing - review & editing. **Chi Keung Marco Lau:** Methodology, Formal analysis.

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