International Review of Financial Analysis 90 (2023) 102894

Contents lists available at ScienceDirect

International Review of Financial Analysis

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

Return-volatility relationships in cryptocurrency markets: Evidence from asymmetric quantiles and non-linear ARDL approach

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ARTICLE INFO

JEL classifications:
C21
G12
G13

Keywords:
Cryptocurrencies
Bitcoin
Ethereum
Implied volatility
Asymmetric quantile regression
NARDL
Asymmetric return-volatility

ABSTRACT

Implied volatility has consistently demonstrated its reliability as a superior estimator of the expected short-term volatility of underlying assets. In this study, we employ the newly constructed robust model-free implied volatility (MFIV) indices for Bitcoin and Ethereum (*BitVol* and *EthVol*) to explore the asymmetric return-volatility relationship of these cryptocurrencies through the lens of behavioral finance theories. Utilizing the asymmetric quantile regression model (QRM) and the Non-linear ARDL (NARDL) approach, our results reveal a notable difference from equities. Both positive and negative return shocks in the cryptocurrency market lead to an increase in volatility. However, during high volatility regimes, positive (negative) return shocks exert a more substantial impact on positive innovations of volatility for Bitcoin (Ethereum) compared to negative (positive) return shocks. The degree of asymmetry steadily intensifies as we progress from medium to uppermost quantiles of the volatility distribution. These observed phenomena can be attributed to behavioral aspects among market participants, including noise trading, behavioral biases, and fear of missing out (FOMO). Our findings hold significant implications for various aspects of cryptocurrency trading, portfolio hedging strategies, volatility derivatives pricing, and risk management.

1. Introduction

The high volatility of cryptocurrencies, compared to other asset classes, remains an ongoing market concern, leading investors, experts, and academics to continually seek further insights into this phenomenon. As of now, the price volatility of cryptocurrencies, particularly that of Bitcoin, is attributed to several factors, including its inelastic supply, lack of an underlying asset, absence of regulatory controls, environmental concerns, information asymmetry, and susceptibility to cyberattacks. Moreover, the commonly accepted notion is that speculation is the main driver of cryptocurrency prices and volatility. In this regard, De la Horra, de la Fuente, and Perote (2019) demonstrate that Bitcoin behaves as a speculative asset in the short term. However, in the long term, speculation does not appear to significantly influence the demand for Bitcoin. Instead, demand might be driven by expectations concerning Bitcoin's future utility as a medium of exchange. These results contradict early evidence on Bitcoin's speculative bubble provided by Cheah and Fry (2015), who claimed that the fundamental price of Bitcoin is zero, as well as by Nicholas Taleb (2021).

In this paper, we take this idea of speculation in the cryptocurrency market and explore the Bitcoin and Ethereum's return-volatility relationship from the behavioral aspects of the market participants. It seems that the cryptocurrencies are still in the price discovery phase. Therefore, understanding the return-volatility relationship in the cryptocurrency market appears to be pivotal. Some recent studies focused on cryptocurrencies' volatility are Cheikh, Zaied, and Chevallier (2020), Katsiampa (2019), Katsiampa, Corbet, and Lucey (2019), Baur and Dimpfl (2018) and Katsiampa (2017).

The return-volatility relationship has been extensively studied in the equity market, and empirical evidence from previous studies indicates

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https://doi.org/10.1016/j.irfa.2023.102894
Received 15 December 2022; Received in revised form 25 July 2023; Accepted 24 August 2023
Available online 25 August 2023

the presence of a negative asymmetric return-volatility relationship in the equity markets (Badshah, 2013; Hibbert, Daigler, & Dupoyet, 2008; Mele, 2007). The negative asymmetric return-volatility relationship phenomenon in the stock market is primarily attributed to two traditional hypotheses: the leverage and feedback theories. These two hypotheses differ in terms of the direction of causality between stock returns and volatility. The next section of this paper will discuss these theories concerning the return-volatility relationship in detail.

However, cryptocurrencies differ from the equity market and are emerging as a distinct asset class. Unlike equities, cryptocurrencies lack a capital structure and underlying assets. As there is no underlying asset, the value of a cryptocurrency primarily hinges on factors such as the prospects of its underlying technology, regulatory acceptance, its role as a store of value, and its function as a medium of exchange. Some recent studies have attempted to elucidate how the markets price cryptocurrencies. For instance, Baur and Dimpfl (2018) demonstrate that cryptocurrency prices are influenced by the fear of missing out (FOMO). Other papers have found evidence of herding behavior in cryptocurrency markets (Ballis & Drakos, 2020; da Gama Silva, Klotzle, Pinto, & Gomes, 2019; King & Koutmos, 2021; Poyser, 2018; Yarovaya, Matkovskyy, & Jalan, 2020). Since cryptocurrencies lack underlying assets and capital structures, unlike equities, the phenomenon of their asymmetric return-volatility relationship cannot be explained using traditional hypotheses such as the leverage and feedback theories. Thus, in this paper, we explore the cryptocurrency return-volatility relationship using behavioral finance theories, which will be discussed in the next section.

In the literature on the return-volatility relationship, various categories of volatility proxies have been used. These include volatility estimation using GARCH family models, market-based (model-free) volatility estimation (i.e., realized volatility), and, notably, implied volatility (IV) estimation using the Black-Scholes models (Karim, Kawsar, Ariff, & Masih, 2022; Karim & Masih, 2021),. However, due to some drawbacks of Black-Scholes implied volatility (BSIV), the model-free implied volatility (MFIV) based on the variance swap methodology has been gaining popularity. Empirical studies have demonstrated the superiority of this model-free implied volatility (MFIV) as it incorporates information on both past volatility and future expected volatility, and is estimated using a full range of option strikes across all moneyness levels. Consequently, the use of implied volatility as a proxy for volatility estimation has been on the rise recently. In this paper, our approach differs from that of Cheikh et al. (2020) and Baur and Dimpfl (2018), and in this study, we delve into the asymmetric return-volatility relationship of cryptocurrencies, particularly Bitcoin and Ethereum, utilizing the recently introduced implied volatility measures, namely *BitVol* and *EthVol*.

Recently, the T3 firm[1] has constructed implied volatility (*IV*) indices of Bitcoin (*BitVol*) and Ethereum (*EthVol*) -implied by the market prices of the options- to better estimate and manage the cryptocurrency risk. These indices are forward-looking measures and provide the short-term expected volatility (30-day implied volatility) of the Bitcoin and Ethereum based on the tradable Bitcoin and Ethereum option prices. The consensus of market participants concerning the future expected volatility of the underlying asset is represented by the options; hence, the implied volatility (*IV)* characterizes the future realized volatility (*RV*) of the underlying assets over the remaining life of the options (Badshah, 2013). As a result, they are often attributed to "*investors' fear gauge*" (Whaley, 2000).

BitVol and *EthVol* are model-free implied volatility (*MFIV*) measures and constructed using the variance swap methodology. Unlike the traditional implied volatility of Black-Scholes (BSIV) at-the-money (ATM), MFIV is constructed using the full range of option strikes (across all moneyness) and provide the best estimation on the expected volatility of Bitcoin and Ethereum. As of June 10th 2022, both Bitcoin (having 41.17% of the total crypto market share) and Ethereum (17.80% of the total crypto market share) and combined they represent 58.97% of the total market share of the cryptocurrency market.[2]

The main objective of this study is to investigate the asymmetric return-volatility relationship of the cryptocurrencies (only Bitcoin and Ethereum), using the newly constructed robust model-free implied volatility (*MFIV*) of the Bitcoin and Ethereum. Moreover, we also aim to extend this investigation to across different volatility regimes (low to high volatility), considering the fact that asymmetry if present may vary depending on the conditional distribution of the volatility. Furthermore, the asymmetric cointegration and long-run asymmetry of the return-volatility relationship of cryptocurrencies are explored. Finally, we try to explain the findings based on behavioral finance theories.

First, in addition to using the standard OLS, we have used the asymmetric quantile regression model (QRM) to investigate the short-run asymmetric return-volatility relationship of the cryptocurrencies at different quantiles of the distribution of the changes of MFIV's because it is more likely that the asymmetric effect is more pronounced at the extreme-tails of the distribution of volatility. One cannot observe these phenomena using the simple OLS since it captures only the mean effect, whereas using the GARCH models is also difficult since this market is exposed to huge shocks which are drastic price movements (Chaim & Laurini, 2018; Charles & Darné, 2019; Cheikh et al., 2020; Trucíos, 2019).

Second, to investigate the co-integration and long-run asymmetry between the volatility level and cryptocurrency prices, we have used the Non-linear Autoregressive Distributed Lag (NARDL). For that, we have used the level form of the data instead of using the return series. The advantage of NARDL is that it can estimate both short- and long-run asymmetry from a single equation. Hence, we can obtain new information such as the cointegration between MFIVs (i.e., *BitVol* and *EthVol*) and the cryptocurrencies (e.g., Bitcoin and Ethereum) prices and the existence of a long-run asymmetry. Moreover, the findings from the NARDL, particularly, the existence of the short-run asymmetry (positive or negative) and the coefficients of a positive-negative relationship, can be compared with the findings derived from the QRM. Third, besides Bitcoin, we have also examined Ethereum (the 2nd largest cryptocurrency by market cap).

Hence, our study makes several contributions to the existing literature. In general, this study contributes to the literature on the behavioral aspects of the cryptocurrency market. More specifically, this study takes the initiative to reveal the asymmetry of the cryptocurrency return-volatility at different quantiles (i.e., low to high volatility regimes) using the model-free implied volatility (*MFIV*) of Bitcoin and Ethereum. This is the first study exploring the asymmetric return volatility using the newly available model free implied volatility of Bitcoin and Ethereum.

This study makes three significant contributions to the existing body of knowledge on the cryptocurrency market. Firstly, it contributes to the identification of the asymmetric relationship between returns and implied volatility in the case of Bitcoin and Ethereum. Consistent with previous findings (Baur & Dimpfl, 2018; Katsiampa et al., 2019), this study reveals that, unlike equity markets (Badshah, 2013; Chakrabarti & Kumar, 2017; Hibbert et al., 2008), both positive and negative returns increase the volatility of cryptocurrencies (Bitcoin and Ethereum) in the short run. In contrast, Cheikh et al. (2020) show that the cryptocurrency market exhibits a positive return-volatility relationship. However, our

[1] "T3 Index is a research-driven financial indexing firm, specializing in volatility and options-related benchmarking. T3 Index is dedicated to developing investible, proprietary indices that track related strategies across a range of asset classes to transform the way people invest and manage risk". The details can be found on https://www.prnewswire.com/news-releases/t3-index-to-launch-a-bitcoin-volatility-index-bitvol-301091318.html

[2] For more detailed information, please refer to https://coin.dance/stats#marketcap

approach is distinct from the above literature in terms of volatility measurement; specifically, we use market implied volatility, a measure not yet employed in studies on cryptocurrencies' return volatility.

Secondly, this study sheds light on the potential impact of the 'good and bad news' effect on cryptocurrency volatility. The presence of noise traders across cryptocurrencies and variations in investors' attention to news related to different cryptocurrencies (Katsiampa et al., 2019) can lead to a positive effect on their volatility. Third, this research provides valuable insights into the asymmetric return-volatility relationship in the cryptocurrency market, considering the use of market implied volatility measures, and highlights the role of news and noise traders in influencing cryptocurrency price volatility.

The study uncovers that positive return-shocks, or good news, have a more pronounced impact on the positive innovation (increase) of Bitcoin's volatility, as measured by changes in BitVol. This effect is particularly evident in the upper quantiles of the volatility distribution, which is synonymous with the high volatility regime. These findings align with the conclusions drawn in the studies by Cheikh et al. (2020) and Baur and Dimpfl (2018), supporting their observations. Conversely, the results differ for Ethereum, where negative return-shocks, or bad news, have a more significant impact on the positive innovation (increase) of Ethereum's volatility during high volatility regimes, as indicated by the upper quantiles of the volatility distribution.

The study also sheds light on the long-run asymmetry using NARDL. The results show that there is strong evidence of asymmetric cointegration between the cryptocurrency prices and the volatility levels. Moreover, our findings show that both negative and positive price movements are associated with a positive innovation (increase) of the volatility in both short- and long-run. However, in the long run, the negative price movement has a greater impact on a positive innovation (increasing) of the volatility for both Bitcoin and Ethereum.

The observed phenomena discussed above are primarily attributed to the behavioral aspects of market participants, including noise trading, behavioral and emotional biases, and the fear of missing out (FOMO). The increase in volatility following a negative return shock is expected. However, the rise in cryptocurrency volatility after a positive return shock (in addition to a negative return shock) can be attributed to the fear of missing out. Since there is no well-established theoretical model for valuing cryptocurrencies, any positive price movement tends to trigger speculative behavior among market participants regarding the future prospects of cryptocurrencies.

Furthermore, investors are prone to engage in noise trading after cryptocurrency prices rise. As a result, Bitcoin exhibits a positive asymmetry (inverted asymmetry) in the short run, particularly during the medium to the highest volatility regimes. Interestingly, this phenomenon of inverted asymmetry is absent in the case of Ethereum. Noise trading activities following a positive price movement are either less or absent for Ethereum. To provide further evidence, we have plotted the trading volumes of Bitcoin and Ethereum following positive and negative return shocks (given in Appendix A). The plots reveal that Bitcoin traders are more active following a high positive return (in response to good news), while Ethereum traders are more active following bad news (when negative return increases). Our findings demonstrate robustness through various estimation approaches and subsample analyses (provided in Tables 5-8).

The remainder of this study is organized as follows. Section 2 discusses the asymmetry of return volatility. Sections 3 and 4 present the data and the methodology, respectively. Section 5 analyzes the empirical results. Section 6 provides the discussion of the results. Finally, Section 7 concludes the paper by offering policy implications and recommendations.

2. Asymmetry of return-volatility

The two competing hypotheses, the leverage and feedback, for the asymmetric return-volatility relationships have been extensively studied in equity markets. Proponents of the leverage hypothesis (Black, 1976; Christie, 1982) assert that the value of a stock declines (increases) due to innovations in the negative (positive) return of the stock. Consequently, the firm's financial leverage increases, and equity holders are exposed to more risk, leading to an increase in the stock's volatility due to the decline in equity value.

On the other hand, advocates of the feedback hypothesis (Bekaert & Wu, 2000; Campbell & Hentschel, 1992; French, Schwert, & Stambaugh, 1987) propose that stock price changes primarily occur because of an increase or decrease in the stock's volatility. This hypothesis is based on the assumption of the existence of a time-varying risk premium in the market, where volatility is not constant but rather priced in the market. Thus, any positive (negative) innovation in the time-varying volatility will lead to a decrease (increase) in the stock price.

Since there is no capital structure in cryptocurrencies, the traditional hypothesis - the leverage and feedback - may not be suitable to be used to explain the asymmetric return-volatility relationship of the cryptocurrency market. To explain the asymmetric return-volatility of Bitcoin and Ethereum, we consider different kinds of biases, such as the representative, effect and extrapolation. In the literature of the equity market, the similar biases have also been used to explain the asymmetric return-volatility relationship of the equity markets. Some recent empirical studies show that the evidence of traditional hypotheses such as the leverage and feedback theories is absent in the equity market (Badshah, 2013; Chakrabarti & Kumar, 2017; Hibbert et al., 2008). Therefore, the asymmetric return-volatility relationship is associated with behavioral finance theories.

Tversky and Kahneman (1974) first mentioned the representative bias (based on the heuristics principles) in describing the quick judgment of the market participants. According to the representative heuristics, people who participate in the market tend to judge the risk and return as representing a good and bad investment. For example, a high return and a low risk represent excellent investments, and, in contrast, a low return and a high risk represent a lousy investment. Therefore, empirical studies show that the relationship between return and volatility is negative in the equity market (Fleming, Ostdiek and Whaley, 1995; Whaley, 2000; Giot, 2005; Andersen, Bollerslev, Diebold, & Ebens, 2001; Bekaert & Wu, 2000; Dennis, Mayhew, & Stivers, 2006; Kim & Kon, 1994). In contrast, Cheikh et al. (2020) show that unlike the equity market, the cryptocurrency market exhibits a positive return-volatility relationship. Their findings imply that the volatility of cryptocurrencies increases in response to good news - a positive innovation in return and volatility decrease in response to bad news - a negative innovation in return. In their studies, the proxy of volatility is estimated using the smooth transition GARCH model. However, another recent study by Baur and Dimpfl (2018) documents contradicting findings. Using the threshold GARCH model, Baur and Dimpfl (2018) find that both positive and negative returns are linked to an increase - a positive innovation - of the cryptocurrency volatility.

Based on the above discussion, we can test the following hypothesis.

H_1. There exists a negative relationship between the returns and volatility of the selected cryptocurrencies.[3]

The negative (positive) asymmetry between the return and volatility can be attributed to the *effect* bias (or the effect heuristics). According to the effect bias, people who participate in the market get swiftly influenced by the current state of emotion. Because of that, they tend to relate the negative (positive) changes of the price as a sign of increasing (decreasing) risk and that is an indication of rising (decreasing)

[3] The following two sub hypotheses are also investigated based on the same discussion$H_{1.1}$: *Changes in implied volatility are only driven by the contemporaneous negative and positive returns of the cryptocurrency.*$H_{1.2}$: *Changes of present implied volatility are also driven by the lag of changes of implied volatility (past changes of implied volatility).*

volatility. Based on the emotion (e.g., fear or greed) of the market participants, a negative price movement can create a bigger response as increasing risk, compared to a positive price movement as a decreasing risk. For the equity market, empirical studies show that a negative price movement has a greater response to the volatility - negative asymmetry (Badshah, 2013; Chakrabarti & Kumar, 2017; Hibbert et al., 2008). This phenomenon is attributed to the theory of loss aversion by Kahneman and Tversky (1979). In contrast, the recent studies of Cheikh et al. (2020) and Baur and Dimpfl (2018) on the cryptocurrency return-volatility exhibit that a positive return shock tends to create a greater response to cryptocurrency volatility, compared to the volatility response to a negative return shock. It seems that good news tends to have more impact on cryptocurrency volatility, compared to bad news. This positive asymmetric (inverted asymmetric) reaction is attributed to the noise trading activity as shown by Baur and Dimpfl (2018). These authors argue that the informed trader trades more after a negative return shock. In contrast, after a positive return shock, noise trading activities dominate the cryptocurrency market due to the fear of missing out (FOMO). Their findings are based on the volatility estimated using the GARCH family models.

Based on the above discussion, we investigate the following hypothesis:

H_2. The impact of positive and negative return shocks on the changes of implied volatility exhibits asymmetry, suggesting the presence of an asymmetric relationship between cryptocurrency returns and volatility.

There are some other biases to explain the above-mentioned phenomenon. For example, the cryptocurrency market has heterogeneous investors investing at different investment horizons with distinctive beliefs, objectives, and investment strategies. The return-volatility estimation (or forecast) varies (underestimate or overestimate) from one market participant to another based on their beliefs. Therefore, the final price in the market could result from the combined activities of those heterogeneous investors. Another kind of bias among the market participants is the extrapolation bias or the extrapolation heuristics. According to the extrapolation bias theory, the market participant tends to extrapolate information from the past events. The judgment is that today's event is the result of past events. Hence, market participants decide by judging past events to represent future events (Chakrabarti & Kumar, 2017; Shefrin, 2008).

Hence, in this paper, we investigate the asymmetry (positive or negative) of return-volatility of the cryptocurrency market at different quantiles – lower to higher quantiles – using the model-free implied volatility (*MFIV*), which is constructed using the variance swap methodology. The MFIVs are forward-looking measures and derived from the tradable Bitcoin and Ethereum option prices. We also investigate if the asymmetric relationship varies across the quantiles of the distribution of the changes of *MFIV*. We expect that the asymmetry will be more pronounced at the upper quantiles of the distribution of the changes of *MFIV*, compared to the lower quantiles of the distribution of the changes of *MFIV*. More specifically, we examine the following hypothesis:

H_3. The impact of positive and negative returns on the changes of implied volatility is different across the quantiles and the degree of the impact is more pronounced at the uppermost quantile (extreme tails) of the volatility distribution.

Moreover, we also investigate if there is any long-run asymmetric relationship between the *MFIV*s and cryptocurrencies (Bitcoin and Ethereum). For that, instead of using the return series (the difference form) of the data, we have used the level form of the data for estimating the non-linear ARDL. One of the shortcomings of NARDL is that, unlike the quantile regression model (QRM), it cannot study the price and volatility relationship at the different conditional distributions of the volatility (the regime independent approach). By deploying the NARDL, the following hypothesis is verified:

H_4. The relationship between the cryptocurrency price and the implied volatility exhibits asymmetry in the long run.[4]

3. Data description

The T3 index recently introduced two new volatility indices (BitVol and EthVol). The Bitcoin 30-day volatility index (BitVol) is introduced in July 2020, and the data is available starting from January 08, 2019. The data for the Ethereum 30-day volatility index (EthVol) is available from April 15, 2020. The tickers for BitVol and EthVol on Refintiv's Eikon terminal are BTCVOL = T3IN and ETHVOL = T3IN. The Bitcoin and Ethereum 30-day volatility indices are constructed using the traded option prices on Bitcoin (BTC) and Ethereum (ETH). For that, the expected variances of two expirations closest to the 30-day time point are linearly interpolated. Options of two subsequent monthly expirations (the 1st and 2nd closest to the point 30 days in the future) are selected for the calculation, and the options in the-money and the far out-of-money are removed in the subsequent step of the calculation.[5] Using the variance swap methodology and the full range of option strikes provides the best estimation for the 30-day expected volatility.

We collected the daily Bitcoin (BTC) and Ethereum (ETH) 30-day volatility data from Refintiv's Eikon terminal from the starting date of the volatility index. For *BitVol*, the daily data is collected from January 08, 2019, to January 08, 2022. For *EthVol*, daily data is collected from April 04, 2020 to January 08, 2022. Following the *BitVol* and EthVol, respective price data of Bitcoin (BTC) and Ethereum (ETH) are collected for the same periods.[6]

Figs. 1 and 2 show the daily closing volatility levels of BitVol and EthVol and their corresponding prices of Bitcoin (BTC) and Ethereum (ETH). Following the World Health Organization (WHO)'s declaration of the virus (Covid-19) outbreak as a public health emergency of international concern on January 30, 2020, the volatility and prices of Bitcoin and Ethereum started to increase to an all-time high. Especially in March 2020, when the major economies worldwide were going for complete lockdowns due to the virus outbreak, Bitcoin (BTC) lost almost half of its value. However, following the price fall, and due to buy at low, the excess buyer-motivated trade increased sharply; hence the Bitcoin (BTC) price also rose sharply. The price of Ethereum was fluctuating between $550 and $750 at the end of 2020. However, after the announcement of Ethereum 2 (new version), the price of Ethereum started to break the previous resistance level and raised to a new all-time high of $1432 on January 19, 2020. Another major event related to the cryptocurrency market was the listing of Coinbase[7] on the NASDAQ stock exchange. Following that, Bitcoin and Ethereum prices reached a new all-time high. Following the significant positive price movement,

[4] By deploying NARDL, we also investigate the following sub hypotheses: ***$H_{4.1}$**: There is an asymmetric cointegration between the cryptocurrency (*i.e.*, Bitcoin and Ethereum) price and the level of implied volatility.**$H_{4.2}$**: The implied volatility and the cryptocurrency price are negatively co-related.**$H_{4.3}$**: The negative price movement has a greater impact on the implied volatility, compared to the positive price movement.*

[5] The detailed calculation process can be found on: https://t3index.com/wp-content/uploads/2020/07/BitVol-Process_Guide_08-July-2020.pdf

[6] We wanted to divide the data into different sub periods (i.e. before and during Covid-19). However, the EthVol data is introduced on 4th April 2020. So, before Covid-19 data is not available.

[7] One of the largest cryptocurrency exchanges that is directly listed on the NASDAQ stock exchange on 14th April 2021. The ticker name is COIN. This is the first and only (till now) cryptocurrency exchange house that has gone public.

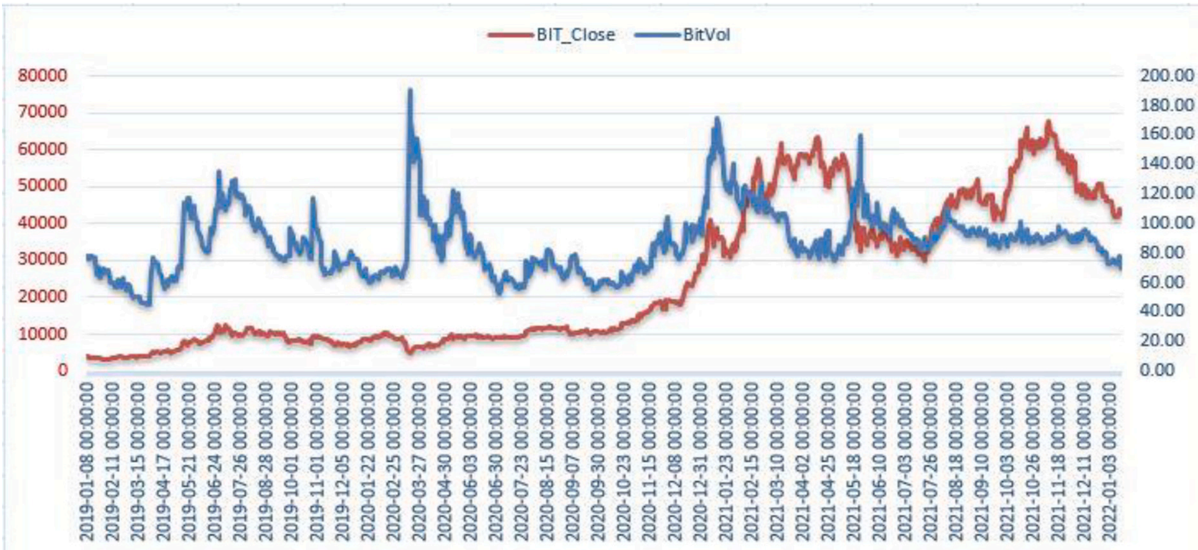

Fig. 1. The trend between Bitcoin and Bitcoin volatility.

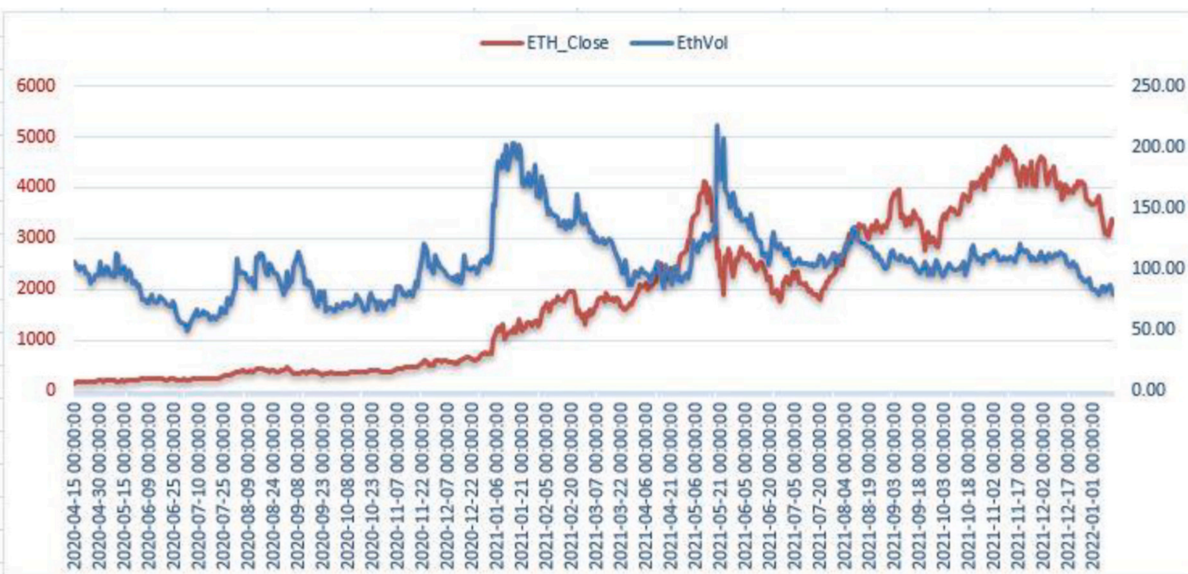

Fig. 2. The trend between Ethereum and Ethereum volatility.

and to gain from the upside of the price, the excess seller-motivated trade raised sharply, compared to the excess buyer-motivated trade. Due to this fact, the cryptocurrency price was falling gradually.

Moreover, the Bitcoin price has fallen sharply after the controversial tweets from Elon Musk.[8] This is because the bitcoin adjusts the tune based on the tone of this wealthiest person, which is labelled as Musk effect on Bitcoin (Huynh, 2022; and Ante, 2023). For example, on May 12, 2020, Musk tweeted that Tesla[9] was no longer accepting Bitcoin for selling the car. Following this news, the Bitcoin price has fallen below $48,000 from $55,000. On May 16, 2020, Musk tweeted that Tesla was selling the Bitcoin that they bought previously. Because of that, the price of Bitcoin has further decreased to $42,000.

From the above discussion, we can see that the cryptocurrencies are one of the most volatile asset classes globally. The good and bad news highly influences their market prices. One of the main reasons is that unlike equity, cryptocurrencies do not have any underlying assets, and their prices are determined based on the pure speculation about the prospect of the underlying technology and the acceptance of the cryptocurrency as a medium of exchange and a payment system (Kaya, 2018). Hence, it is crucial to study the cryptocurrency return-volatility relationship to make an informed decision on trading, investment and policy recommendation.

Following Badshah (2013), we have calculated the daily percentage continuously compounded returns (denoted by *BTC R* and *ETH R* in Table 1) of Bitcoin (*BTC*) and Ethereum (*ETH*) using the formula (Eq. 1):

$$100 \times (log(P_t) - log(P_{t-1})) \quad (1)$$

The daily percentage returns of BitVol and EthVol (denoted by Δ

[8] Elon Musk is the "founder, CEO, and Chief Engineer at SpaceX; early-stage investor, CEO, and Product Architect of Tesla, Inc.; founder of The Boring Company; and co-founder of Neuralink and OpenAI. A centibillionaire, Musk is one of the richest people in the world." https://en.wikipedia.org/wiki/Elon_Musk

[9] Tesla, Inc. is an American electric vehicle and clean energy company based in Palo Alto, California and is founded by Elon Musk.

Table 1
Descriptive statistics of the variables' returns.

	ΔBVOL	BTC R	ΔEVOL	ETH R
Mean	0.1806	0.2551	0.1283	0.4838
Median	−0.4905	0.1780	−0.5353	0.3756
Max	75.6974	21.5423	68.5533	32.4082
Min	−25.6149	−30.9314	−20.6794	−27.8909
SD	6.5379	4.2566	6.1618	5.2761
Skewness	3.1273	−0.2931	2.8887	0.0173
Kurtosis	30.7157	8.7201	29.7225	9.5150
Jarque-Bera	31,000	1281	20,000	1109
P-Value	0.000	0.000	0.000	0.000
ADF	−22.901***	−22.170***	−28.186***	−28.046***
Number Obs	931	931	628	628

Notes. We provide the descriptive statistics of the return and volatility of Bitcoin, Ethereum, respectively. *BTC R* and *ETH R* are the percentage continuous compounding returns of Bitcoin and Ethereum. Δ*BVOL* and Δ*EVOL* are the percentage changes of the Bitcoin and Ethereum-volatility. We conduct the unit-root test Augmented Dickey-Fuller (ADF) to assess non-stationarity, and the Jarque-Bera statistics to check for normality. The ADF test rejects the null hypothesis at the 1% significance level as denoted by ***.

EVOL and Δ*BVOL* in Table 1) are calculated as (Eq. 2):

$$100 \times \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) \tag{2}$$

The summary statistics and the tests for normality and unit-roots for the variables mentioned above are also given in Table 1. The mean return of Ethereum is comparatively higher than the mean return of Bitcoin during our sample periods. The mean of the volatility changes denoted by Δ*EVOL* and Δ*BVOL* are almost the same but slightly higher for Ethereum. The test for skewness and kurtosis shows that the Bitcoin return is negatively skewed, and the Ethereum return is positively skewed, whereas all the volatility indices' returns are positively skewed. Moreover, all the variables exhibit the leptokurtic, picked curve (positive kurtosis) concerning the normal distribution. Hence, the Jarque-Bera statistics also reject the normality for each of the variables stated in Table. 1. The last 2nd row of Table 1 shows the unit-roots test (using the Augmented Dickey-Fuller). The results show that all the four variables given in Table 1 are stationary (they reject the null hypothesis of non-stationary at the 1% level). However, all the variables are non-stationary in their level form. Therefore Bitcoin, Ethereum, *BitVol*, and *EthVol* are all I(0) variables.

4. Methodology

4.1. Quantile regression

This study applies the Quantile Regression Method (QRM) which was developed by Koenker and Bassett Jr (1978), and later reviewed and revised by Buchinsky (1998); Koenker and Hallock (2001); and Koenker (2005), followed by the broader application in the finance and banking literature (Arribas, Peiró-Palomino, & Tortosa-Ausina, 2020; Behr, 2010; Covas, Rump, & Zakrajšek, 2014; Schaeck, 2008). The advantage of applying the quantile regression is to understand the relationship between the variables outside the mean of the data to help understand the findings in the absence of the normal distribution and the presence of a Non-linear relationship. Thus, this method provides a greater flexibility than other regression methods to identify the heterogeneous relationships at different parts of the distribution of the outcome variable. All in all, the usage of the method offers features, i.e. robustness to the outlier and equibalance to monotonous transformation (Gilchrist, 2000), that make this method useful to identify some stylized facts in the absence of linearity assumption. Therefore, this study uses quantile regression to allow the slope coefficient to vary across the quantiles and asymmetries of the dependent variable. We expect that the asymmetry will be heterogeneous across the quantiles (from the lower to upper quantiles) of the distribution of MFIV. That is because the market has heterogeneous investors with different beliefs, extrapolation biases, objectives, and investment strategies, making them invest at different investment horizons.

Alike previous studies (e.g., Badshah, Frijns, Knif, & Tourani-Rad, 2016; Das & Kannadhasan, 2020; You, Guo, Zhu, & Tang, 2017) use this method in the financial market arena to explore the asymmetric patterns at the different quantiles of the distribution of the dependent variable. This study uses an asymmetric quantile regression model to examine the cryptocurrency's asymmetric (positive or negative) return-volatility relationship at different quantiles of the distribution of MFIV. We start with the mean-regression method, which is process-wise similar to that of Low (2004); Giot (2005); Badshah et al. (2016); Das and Kannadhasan (2020). We consider the mean regression as the benchmark for our analysis.[10] Then, we extend this mean-regression model by incorporating the asymmetric relation, using the quantile regression model to investigate whether the changes of *MFIV* are affected heterogeneously by the positive and negative cryptocurrency returns (Eq. 3) across the distribution of *MFIV*.

Here, we define $\Delta MFIV_{it}$ as the percentage change in volatility (Eq. 4) and R_{it} as the daily percentage continuously compounded return of cryptocurrency *i*where *i*=Bitcoin, and Etherum where

$$R_{it}^{+} = \begin{cases} R_{it} \text{ if } R_{it} > 0 \\ 0 \text{ if } R_{it} < 0 \end{cases} \text{ and } R_{it}^{-} = \begin{cases} R_{it} \text{ if } R_{it} < 0 \\ 0 \text{ if } R_{it} > 0 \end{cases} \tag{3}$$

For the asymmetric relation, the standard mean-regression model will have the following form (Eq. 4),

$$\Delta MFIV_{it} = \alpha + \sum\nolimits_{L=1}^{3} \beta_{i\,L} \Delta MFIV_{it-L} + \sum\nolimits_{L=0}^{3} \gamma_{i\,L}\, R_{it-L}^{+} + \sum\nolimits_{L=0}^{3} \delta_{i\,L}\, R_{it-L}^{-} + u_t \tag{4}$$

Here, α is the intercept, β_{iL} represents the coefficient of the Δ*MFIV* in volatility *i*where lag L = 1–3. The coefficient γ_{iL} indicates the positive return of the cryptocurrency *i*, whereas the coefficient δ_{iL} Indicates the negative return of cryptocurrency. Here, L = 0–3 is applied for both types of returns. The error term u_t is assumed to have independent and identical distribution with a zero mean. Next, we move forward to the quantile regression properties to capture the vital information across the quantiles. This capture of additional information cannot be done with the mean-regression method as it assumes that the effect of the cryptocurrency return is static across the changes of the response variable. To examine the asymmetric relation at different quantiles, we will have the following form of the equation (Eq. 5)

$$\Delta MFIV_{it} = \alpha^{(q)} + \sum\nolimits_{L=1}^{3} \beta_{iL}^{(q)} L \Delta MFIV_{it-L} + \sum\nolimits_{L=0}^{3} \gamma_{iL}^{(q)} R_{it-L}^{+} + \sum\nolimits_{L=0}^{3} \delta_{iL}^{(q)} R_{it-L}^{-} + u_t \tag{5}$$

Here, $\alpha^{(q)}$ is the intercept of the respective quantile, $\beta_{iL}^{(q)}$ is the coefficient of lagged Δ*MFIV* in the volatility index *i*, where the lagged L = 1–3. The coefficient $\gamma_{iL}^{(q)}$ and $\delta_{iL}^{(q)}$ represents the positive and negative return of cryptocurrency, respectively, where the lagged L = 0–3 are used for both positive and negative returns. The error term u_t is assumed to have independent and derived from the error distribution of $\varnothing_q u_t$ with a zero mean at the q^{th} quantile. The main feature of this quantile regression is that it provides the effect captured by $\beta_{iL}^{(q)}$, $\gamma_{iL}^{(q)}$ and $\delta_{iL}^{(q)}$ at each quantile with a range of $q \in (0,1)$. The heteroscedasticity is now allowed in the error u_t, thereby providing different coefficients for the different quantiles. Thus, we estimate our model following this quantile regression method of Koenker & Bassett Jr, 1978).

[10] The studies of Low, (2004) and Giot, (2005) are among the first few to examine the return-volatility relation and conclude the presence of the asymmetric and non-linear relations, thus relating their findings to specific behavioral aspects (i.e., the loss aversion nature).

4.2. Non-linear ARDL

We use the non-linear Autoregressive Distributed Lag (henceforth, NARDL) to address the possibility of asymmetric non-linear adjustments to the equilibrium. We believe that the deviations from the equilibrium are asymmetric and non-linear in nature. This is because the factors contributing to non-linearity can also contribute to asymmetric deviations from the equilibrium (Nam, Pyun, & Arize, 2002). The NARDL model more recently advanced by Shin, Yu, and Greenwood-Nimmo (2014) provides overreaching advantages in comparison with other approaches in allowing for short-and long-run asymmetry. This means that NARDL, based on the consideration of dynamic error-correction associated with the attribute of asymmetric long-run cointegrating regression, exhibits the relationship of short-and long-run asymmetries. Thus, it offers the parameter to quantify the magnitude of the responses of the dependent variable to the positive and negative shocks of the independent variable. In addition, the NARDL model is believed to provide robust estimates in implementing the cointegration tests, while dealing with small samples in the study. Plenty of time-series studies in the context of macroeconomy use this model to examine whether the effect of positive and negative changes of regression has different (not identical) influences on the regress and (Amin, Anwar, & Liu, 2022; Arize, Malindretos, & Igwe, 2017; Nusair & Olson, 2021; Sukmana & Ibrahim, 2017).

Accordingly, we employ the NARDL model developed by Shin et al. (2014) as the asymmetric addition to the ARDL model developed by Pesaran and Shin (1995) and Pesaran, Shin, and Smith (2001). We start with the following equation, which considers the subset of regressors included in the long run relationship.

$$MFIV_{jt} = \alpha_{j0} + \alpha_{j1}R_{jt}^{+} + \alpha_{j2}R_{jt}^{-} + e_{jt} \tag{6}$$

Here, j=Bitcoin, and Etherum, $MFIV_{jt}$ is the model-free implied volatility constructed based on the cryptocurrencies separately, R_{jt} is the cryptocurrency return rate. The vector of long-run parameters i.e., α_{j0}, α_{j1}, and α_{j2} to be estimated. The stationary mean-zero error term e_{jt} represents the deviation from the long-run equilibrium. R_{jt}^{+} and R_{jt}^{-} represent the partial sum process that captures the positive and negative changes in R such as:

$$R_{jt}^{+} = \sum_{n=1}^{t} \Delta R_{jt}^{+} = \sum_{n=1}^{t} max(\Delta R_n, 0) \tag{7}$$

$$R_{jt}^{-} = \sum_{n=1}^{t} \Delta R_{jt}^{-} = \sum_{n=1}^{t} min(\Delta R_n, 0) \tag{8}$$

In the empirical setting, Eq. (4) can be transformed into an asymmetric NARDL according to Shin et al. (2014) by including asymmetric short-and long-run parameters:

$$\begin{aligned}\Delta MFIV_{jt} = {} & \beta_{j0} + \beta_{j1}MFIV_{jt-1} + \beta_{j2}R_{jt-1}^{+} + \beta_{j3}R_{jt-1}^{-} + \sum_{i=1}^{p} \varphi_{ji}\Delta R_{jt-i} \\ & + \sum_{i=0}^{q}\left(\theta_{ji}^{+}\Delta R_{jt-i}^{+} + \theta_{ji}^{-}\Delta R_{jt-i}^{-}\right) + e_{jt}\end{aligned} \tag{9}$$

The additional p and q are the lag orders, and the rest of the variables are defined as before. We can now identify both the long-run parameters and the asymmetric effect of the cryptocurrency rates of returns on volatility.

We apply the procedures as in Fousekis, Katrakilidis, and Trachanas (2016) and Sukmana and Ibrahim (2017) by starting with the estimation of Eq. (7), using the ordinary least square method. To determine the presence of cointegration between the variables, we apply the F-test denoted as F_{PSS} to test the null hypothesis of H_O: $\rho = 0 = \beta_{j1} = \beta_{j2} = \beta_{j3}$ (Pesaran et al., 2001) or the t-test denoted as T_{BDM} to test the null hypothesis of H_0: $\rho = 0$ (Banerjee, Dolado, & Mestre, 1998). This is accomplished to conclude that the model is not suffering from the presence of insignificant lags. With the confirmation of the presence of a long-run relationship, we proceed to test the hypotheses $H_0 : -\beta_{j2}/\beta_{j1} = -\beta_{j3}/\beta_{j1}$ for the long-run asymmetry and $H_0 : \sum_{i=0}^{q}\theta_{ji}^{+} = \sum_{i=0}^{q}\theta_{ji}^{-}$ for the short-run asymmetry.

Finally, we also graph the asymmetric dynamic cumulative multiplier effect of one percentage point change in positive and negative in R to visually present the asymmetric relationship between the variables, as follows in the equation

$$m_{jh}^{+} = \sum_{m=0}^{h} \frac{\partial MVIF_{jt+m}}{\partial R_{jt}^{+}}, m_{jh}^{-} = \sum_{m=0}^{h} \frac{\partial MVIF_{jt+m}}{\partial R_{jt}^{-}}, h = 0, 1, 2, \tag{10}$$

Note that as $h \rightarrow \infty, m_{jh}^{+} \rightarrow \alpha_{j1}\, and\, m_{jh}^{-} \rightarrow \alpha_{j2}$ by construction, where α_1+ and α_2-, symbolize the asymmetric long-run coefficients.

5. Empirical results

5.1. Findings using QRM

Asymmetric quantile regression results for the Bitcoin return with the changes of the *BitVol* index are given in Fig. 3. We have a total of 12 covariates, including an intercept, and they are plotted for a total of eleven different quantiles (quantiles q ranging from 0.05, 0.1…, 0.9, and 0.95). The solid curves within the grey shaded area (the confidence interval) are the estimated coefficients from the quantile regression, and the vertical dashed lines within the two dotted lines (the confidence interval) are the estimated coefficients from the OLS. The X-axis represents the quantiles (q), and the Y-axis presents the percentage of the covariate effect. They can be interpreted as the effect of the independent variables on the changes of Bitcoin volatility in a percentage-point. The right-hand side (the independents variables) denoted by *L1Y*, *L2Y* and *L3Y*[11] are the lags of the dependent variable (Changes of *BitVol*), *pCCRBTC* represents positive continuous compounding return of Bitcoin. *L1P*, *L2P*, and *L3P* are the lags of the *pCCRBTC*. Finally, *nCCRBTC* represents the negative continuous compounding return of Bitcoin. *L1N*, *L2N*, and *L3N* are the lags of the *nCCRBTC*.

The estimated coefficients given in Fig. 3 are tabulated in Table 2 for the upper and lower quantiles. The standard errors are given in the parentheses, and the stars denote the levels of statistical significance of the coefficients (* significant at 10%, ** significant at 5%, and *** significant at 1%). For each of the quantile estimates, the robust t-statistics are obtained using the bootstrap method. For the OLS, the standard errors are corrected (using the robust standard errors) for the heteroskedasticity problem.

In Table 2,$\Delta BVOL_{t-1}$, $\Delta BVOL_{t-2}$ and $\Delta BVOL_{t-3}$ represent the lags of the changes of the *BITVOL*. The positive return of the Bitcoin is denoted by R_t^{+} and the negative return is denoted by R_t^{-}. For both positive and negative returns, we have selected three lags. From the estimated contemporaneous coefficients given in columns 5 and 9, we can see that the relationship between changes of Bitcoin's implied volatility and return are positive across the quantiles. The coefficients of R_t^{+} are positive, so R_t^{+} increases *BitVol*. The coefficients of R_t^{-} are negative, and hence R_t^{-} also increases BitVol. The result shows that the increase in the positive and negative returns also increases the volatility but the impact of the positive return on volatility is much higher during high volatility regimes – denoted by the uppermost quantiles. For example, the coefficients estimated at q = 0.95 quantile (and OLS) show that a 1% increase in Bitcoin's return is associated with a 1.243% (0.530%) increase in Bitcoin's volatility. In contrast, a 1% decrease in Bitcoin's return is linked to a 0.832% (0.567%) increase in Bitcoin's volatility. These results are significant at the 1% level. It implies that, for Bitcoin, unlike equity, both good and bad news lead to an increase in Bitcoin's implied

[11] The number of lags is selected based on the AIC and SBIC criteria.

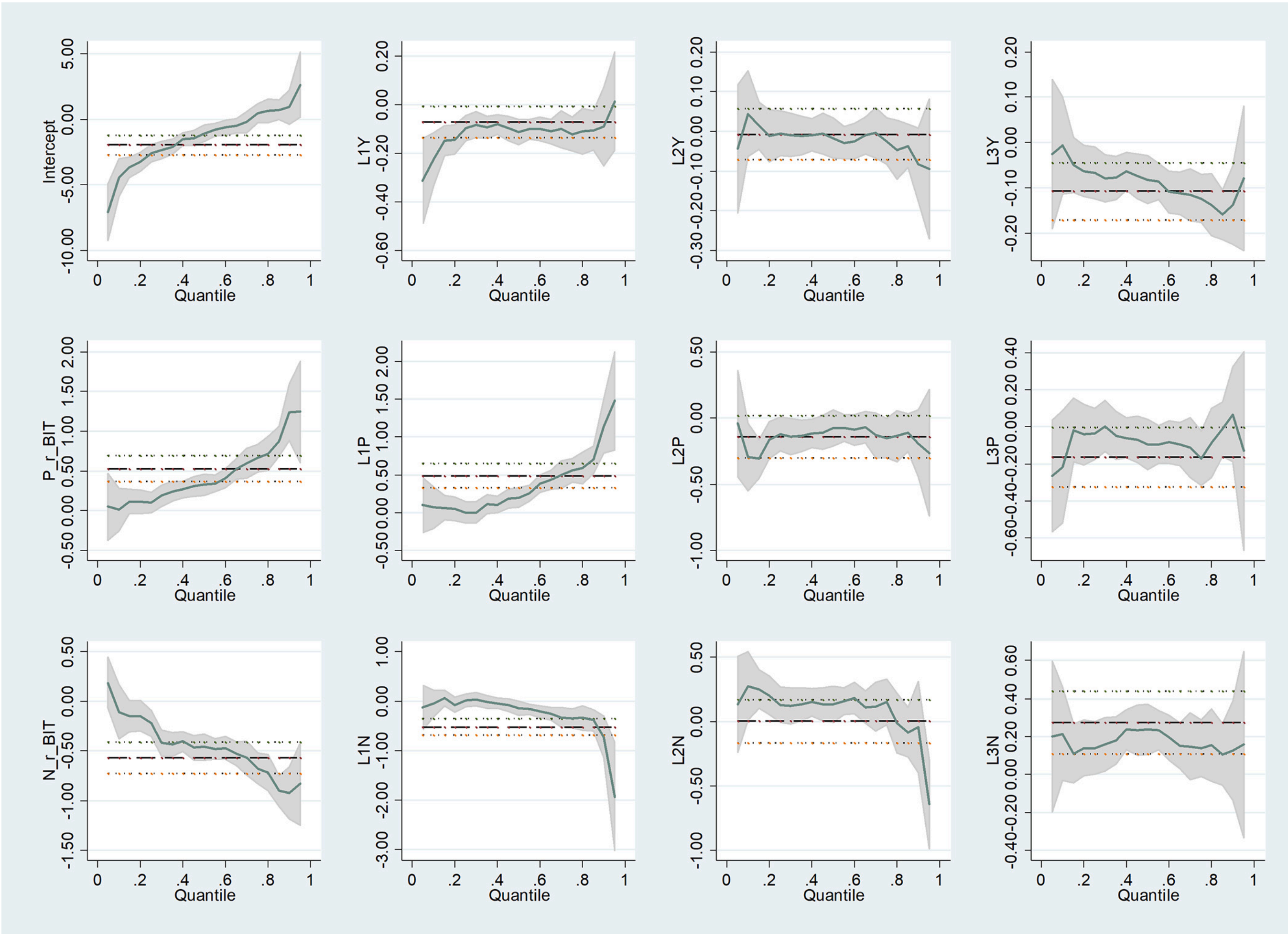

Fig. 3. Quantile regression estimation plots (changes of *BITVOL* is the dependent variable).

volatility (*BitVol*). This finding rejects *Hypothesis 1*, which claims that the Bitcoin's return-volatility are negatively co-related.

However, the impact of positive returns is much higher than the impact of negative returns on the changes in Bitcoin's volatility. Hence, this finding supports *Hypothesis 2,* which claims that the impacts of positive and negative returns on the changes of implied volatility are not the same; hence, there is an *asymmetric* relationship between Bitcoin's return and volatility. We also can see that, as we move to uppermost quantiles, the difference between the coefficients of positive and negative returns (R_t^+ and R_t^-) increase monotonically. It implies that the marginal effects of positive and negative returns are much higher at the upper quantiles. The positive asymmetric effect is much more significant at the upper quantiles (high volatility regimes) of the distribution of the changes of *BitVol.* One cannot observe this phenomenon using the simple OLS since it captures only the mean effect. It accepts *Hypothesis 3,* which claims that the impacts of the positive and negative returns on the changes of implied volatility are different across the quantiles and the degree of the impact is more pronounced at the uppermost quantile (extreme tails) of the volatility distribution. Interestingly, in most of the cases, from the median to the lower quantiles, the impacts of bad and good news (positive and negative retunes) are insignificant. It implies that during the low to medium volatility regimes, there is no asymmetric relationship between Bitcoin's return and volatility. It is interesting to see how the estimated coefficients vary with the distribution of the changes of volatility.

Moreover, the sizes of the contemporaneous coefficients (R_t^+ and R_t^-) are higher (and significant at the 1% level) compared to the sizes of the coefficients of the lagged variables except for the coefficients of the highest quantile ($q = 0.95$). After the first lag, the impacts of lag-returns (second and third lags) mostly became insignificant. It implies that there is auto correlation up to one lag. Hence, we can reject *Hypothesis1.1.* The rejection says that the changes of implied volatility are only driven by the contemporaneous negative and positive returns of Bitcoin. Moreover, the first-lag of the changes of implied volatility (the dependent variable) is also significant at the lower to medium quantiles. Hence, it also supports *Hypothesis 1.2.* It argues that the changes of present implied volatility are also driven by the *lag* of changes of implied volatility (past changes of implied volatility).

The main findings are summarized as follows. Unlike equity, both positive and negative returns of Bitcoin are associated with the positive innovation (increase) of volatility. This result supports the findings of Baur and Dimpfl (2018), where this phenomenon can be attributed to the fear of missing out (FOMO). Moreover, our results indicate that during high volatility regimes (represented by upper quantiles), changes of Bitcoin's volatility are more linked to the positive return than the negative return. It means, at upper quantiles, the impact of the good news on the positive innovation of *BitVol* is much higher, compared to the impact of bad news on the positive innovation of *BitVol.* In contrast, during the calm volatility periods (represented by the median-lower quantiles), the relationship between changes of volatility and positive-negative return are mostly insignificant. We can argue that the market participants' reactions to Bitcoin's positive return-shock are higher,

Table 2
Testing the changes of Bitcoin volatility across the quantiles.

Quantile	$\Delta BVOL_{t-1}$	$\Delta BVOL_{t-2}$	$\Delta BVOL_{t-3}$	R_t^+	R_{t-1}^+	R_{t-2}^+	R_{t-3}^+	R_t^-	R_{t-1}^-	R_{t-2}^-	R_{t-3}^-	Intercept	R^2
0.05	−0.312***	−0.0441	−0.0249	0.0483	0.100	−0.0437	−0.266	0.184	−0.130	0.135	0.199	−7.058***	0.0953
	(−4.06)	(−0.58)	(−0.33)	(0.25)	(0.52)	(−0.22)	(−1.38)	(0.96)	(−0.66)	(0.68)	(1.00)	(−7.85)	
0.1	−0.224***	0.0439	−0.00554	0.0133	0.0668	−0.293*	−0.217	−0.107	−0.0473	0.278	0.213	−4.458***	0.0627
	(−3.93)	(0.77)	(−0.10)	(0.09)	(0.47)	(−2.03)	(−1.51)	(−0.75)	(−0.32)	(1.89)	(1.43)	(−6.68)	
0.15	−0.149***	0.0143	−0.0489	0.114	0.0621	−0.308**	−0.0176	−0.148	0.0638	0.254*	0.109	−3.676***	0.0507
	(−3.83)	(0.37)	(−1.28)	(1.18)	(0.64)	(−3.12)	(−0.18)	(−1.52)	(0.64)	(2.52)	(1.08)	(−8.06)	
0.2	−0.143***	−0.0116	−0.0628	0.111	0.0479	−0.166*	−0.0426	−0.146	−0.0779	0.205*	0.138	−3.257***	0.0438
	(−4.34)	(−0.35)	(−1.94)	(1.36)	(0.58)	(−1.98)	(−0.51)	(−1.77)	(−0.92)	(2.40)	(1.61)	(−8.43)	
0.25	−0.0966**	−0.00519	−0.0660*	0.101	0.00235	−0.122	−0.0377	−0.222**	0.00905	0.132	0.138	−2.578***	0.0373
	(−3.29)	(−0.18)	(−2.30)	(1.39)	(0.03)	(−1.64)	(−0.51)	(−3.02)	(0.12)	(1.74)	(1.81)	(−7.50)	
Median	−0.113***	−0.0174	−0.0814***	0.328***	0.200***	−0.0782	−0.0957	−0.461***	−0.145*	0.134*	0.235***	−1.082***	0.0522
	(−4.65)	(−0.72)	(−3.43)	(5.45)	(3.30)	(−1.27)	(−1.57)	(−7.60)	(−2.34)	(2.14)	(3.73)	(−3.81)	
0.75	−0.121**	−0.0249	−0.123***	0.661***	0.557***	−0.152	−0.171	−0.675***	−0.352***	0.153	0.137	0.456	0.1054
	(−3.19)	(−0.66)	(−3.32)	(7.05)	(5.88)	(−1.58)	(−1.79)	(−7.12)	(−3.63)	(1.56)	(1.39)	(1.03)	
0.8	−0.108**	−0.0468	−0.137***	0.719***	0.589***	−0.138	−0.0880	−0.718***	−0.340***	−0.0138	0.155	0.641	0.1231
	(−2.78)	(−1.21)	(−3.60)	(7.47)	(6.06)	(−1.40)	(−0.90)	(−7.38)	(−3.42)	(−0.14)	(1.54)	(1.41)	
0.85	−0.106	−0.0373	−0.159**	0.873***	0.701***	−0.114	−0.0121	−0.903***	−0.388**	−0.0827	0.103	0.725	0.1432
	(−1.94)	(−0.68)	(−2.97)	(6.45)	(5.13)	(−0.83)	(−0.09)	(−6.61)	(−2.77)	(−0.59)	(0.72)	(1.13)	
0.9	−0.0904	−0.0835	−0.137	1.237***	1.144***	−0.194	0.0676	−0.925***	−0.724***	−0.0394	0.125	0.932	0.1729
	(−1.20)	(−1.11)	(−1.86)	(6.60)	(6.04)	(−1.01)	(0.35)	(−4.89)	(−3.74)	(−0.20)	(0.64)	(1.05)	
0.95	0.0152	−0.0950	−0.0788	1.243***	1.478***	−0.265	−0.131	−0.832*	−1.927***	−0.642	0.158	2.651	0.2372
	(0.10)	(−0.65)	(−0.55)	(3.42)	(4.02)	(−0.71)	(−0.35)	(−2.26)	(−5.13)	(−1.69)	(0.41)	(1.54)	
OLS	−0.0694	−0.00744	−0.107**	0.530***	0.487**	−0.141	−0.164	−0.567***	−0.518	0.00436	0.274**	−1.937***	0.1437
	(−0.83)	(−0.24)	(−3.21)	(3.33)	(2.66)	(−1.82)	(−1.86)	(−5.27)	(−1.53)	(0.02)	(2.71)	(−3.34)	

Notes. We provide findings from the lower to upper (i.e., 0.05 to 0.95) quantile regressions and the OLS regression of the changes of *BITVOL* on the set of independent variables. $\Delta BVOL_{t-1}$, $\Delta BVOL_{t-2}$ and $\Delta BVOL_{t-3}$ represent the lags of the changes of *BITVOL*. The positive return of the Bitcoin is denoted by R_t^+ while the negative return of this crypto currency is denoted by R_t^-. Note that R_{t-1}^+, R_{t-2}^+ and R_{t-3}^+ are the lags of the positive returns. R_{t-1}^-, R_{t-2}^- and R_{t-3}^- are the lags of the negative returns. The significance levels at 1%, 5% and 10% are denoted by ***, ** and *, respectively. The t-statistics are given in parentheses.

compared to negative return-shock during high volatility regimes. It implies that following the positive return shock, the excess buyer-motivated trade increases due to the fear of missing out (FOMO). In Appendix A, we have provided further evidence to that. As a result, for hedging the risk, the excess demand on Bitcoin's options due to a positive return-shock is much higher than the excess demand of options following a negative return-shock. Tables 7-8 demonestrate robustness of the findings through subsample analyses.

A similar analysis is carried out for Ethereum, the 2nd largest cryptocurrency by market capitalization. Even though the underlying technology and the scope of usage of Etherum are slightly different from Bitcoin, the purpose of the market participants in trading and holding Ethereum is still the same as Bitcoin. Hence, we expect to get similar results that we have already discussed for the Bitcoin above. However, a slightly different finding may appear because of the marginally different expectations of the market participants from Ethereum compared to Bitcoin.

Fig. 4, the same as Fig. 3, presents the asymmetric quantile regression results for the Ethereum return with the changes of the *EthVol* index. We can see the shapes of Fig. 3 and Fig. 4 look the same. Some of the findings are a bit different from the results discussed for the asymmetric relationship between Bitcoin and *BitVol*. For more details, the estimated coefficients of some of the critical quantiles (i.e., 0.05 to 0.95) from Fig. 4 are tabulated in Table 3. Like the findings on Bitcoin discussed earlier, and unlike equity, both positive and negative returns of the Ethereum are strongly linked to positive innovation of the volatility. As the case for Bitcoin, we can also see that impacts of the positive and negative returns of Ethereum on the positive innovation of the implied volatility of Ethereum (*EthVol*) are increasing monotonically from medium to the uppermost quantiles. Moreover, the impacts of the contemporaneous returns (represented by R_t and R_t^-) on the changes of volatility are much higher and significant at the 1% level compared to the lagged effect.

However, unlike Bitcoin during the high volatility regimes, the positive innovation (increase) in the volatility of Ethereum is more pronounced to the negative return-shock. It implies that the bad news has a greater impact on the positive innovation of the Ethereum volatility at the uppermost qualities of the distribution of the volatility changes. It also implies that following the negative return shock, the excess buyer-motivated trade increases to take advantage at a lower price (buying at a lower price). In Appendix A, we have provided further evidence to that. As a result, for hedging the risk, the excess demand of options due to a negative return-shock is much higher than the excess demand of options following a positive return-shock. Moreover, the impact of the positive and negative returns of Ethereum on the volatility changes is mainly found to be insignificant from the lowermost to medium quantiles (during calm periods). The reaction of the market participants tends to vary depending on the gravity of the cryptocurrency return-shock. In addition, a subsample analyses is given in Tables 5-6 for robustness checking.

For a closer look, in Figs. 5 and 6, we report the impact of the cotemporaneous positive and negative returns (represented by R_t^+

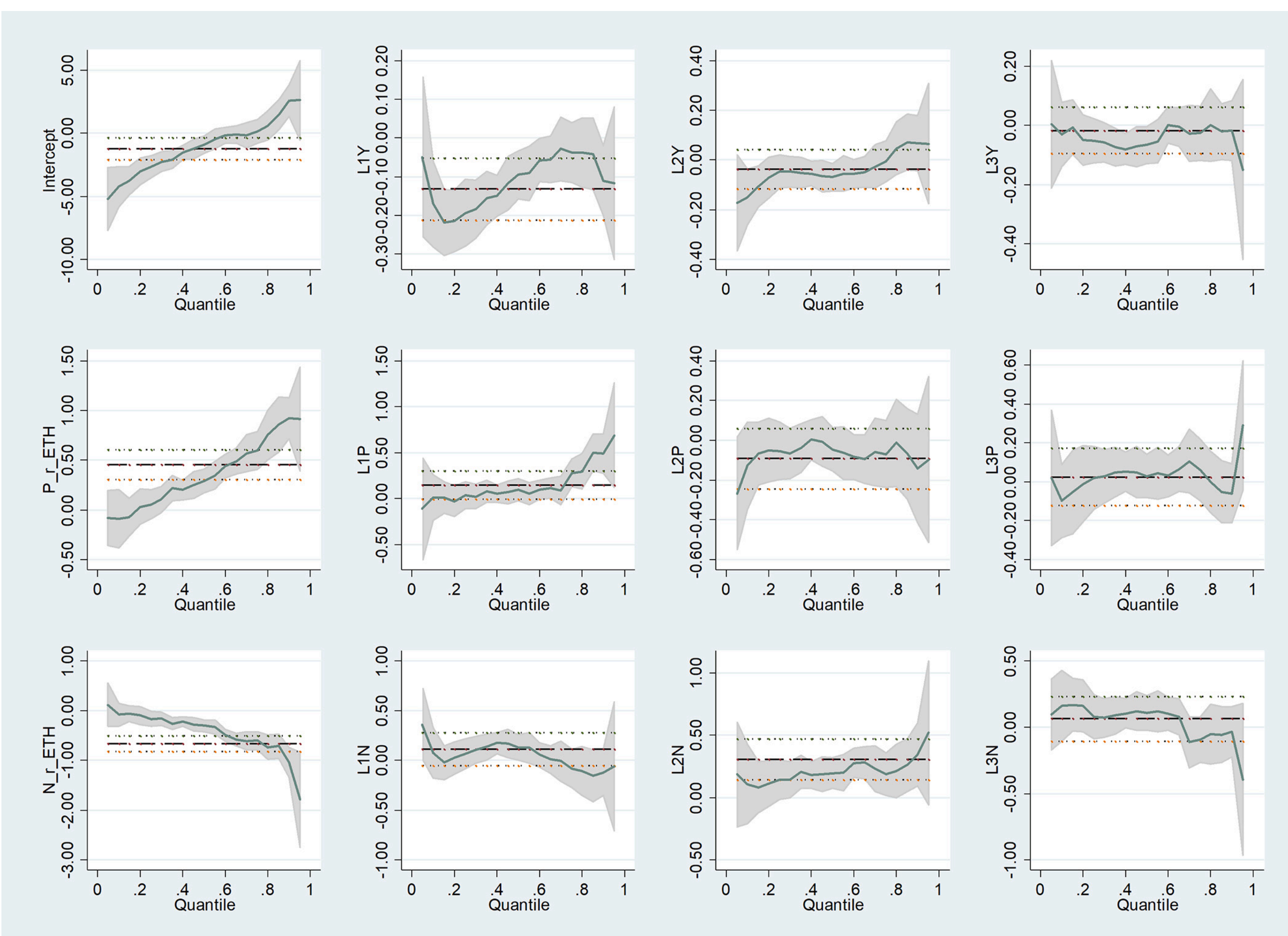

Fig. 4. Quantile regression estimation plots (changes of *ETHVOL* is the dependent variable).

Table 3
Testing the changes of Ethereum volatility across the quantiles.

Quantile	$\Delta EVOL_{t-1}$	$\Delta EVOL_{t-2}$	$\Delta EVOL_{t-3}$	R_t^+	R_{t-1}^+	R_{t-2}^+	R_{t-3}^+	R_t^-	R_{t-1}^-	R_{t-2}^-	R_{t-3}^-	Intercept	R^2
0.05	−0.0492	−0.173	0.00454	−0.0793	−0.111	−0.267	0.0192	0.119	0.362	0.184	0.0941	−5.215***	0.0992
	(−0.49)	(−1.73)	(0.05)	(−0.41)	(−0.57)	(−1.39)	(0.10)	(0.60)	(1.73)	(0.89)	(0.44)	(−4.67)	
0.1	−0.170**	−0.149*	−0.0306	−0.0901	0.0128	−0.128	−0.0986	−0.0854	0.0713	0.107	0.162	−4.222***	0.0689
	(−2.64)	(−2.32)	(−0.48)	(−0.73)	(0.10)	(−1.04)	(−0.82)	(−0.67)	(0.53)	(0.81)	(1.18)	(−5.88)	
0.15	−0.218***	−0.107*	−0.00597	−0.0711	0.0149	−0.0671	−0.0526	−0.0645	−0.0237	0.0827	0.169	−3.788***	0.048
	(−5.02)	(−2.47)	(−0.14)	(−0.86)	(0.18)	(−0.81)	(−0.65)	(−0.76)	(−0.26)	(0.92)	(1.83)	(−7.83)	
0.2	−0.215***	−0.0720	−0.0492	0.0331	−0.0277	−0.0496	−0.0120	−0.0999	0.0240	0.111	0.161	−3.047***	0.0379
	(−4.95)	(−1.67)	(−1.15)	(0.40)	(−0.33)	(−0.60)	(−0.15)	(−1.17)	(0.27)	(1.24)	(1.75)	(−6.32)	
0.25	−0.193***	−0.0467	−0.0536	0.0563	0.0363	−0.0552	0.0189	−0.169*	0.0644	0.144	0.0762	−2.664***	0.037
	(−5.00)	(−1.21)	(−1.40)	(0.76)	(0.49)	(−0.74)	(0.26)	(−2.23)	(0.80)	(1.80)	(0.93)	(−6.19)	
Median	−0.0956*	−0.0698	−0.0669	0.288***	0.0950	−0.0466	0.0297	−0.301***	0.129	0.196*	0.106	−0.922*	0.044
	(−2.51)	(−1.84)	(−1.78)	(3.98)	(1.30)	(−0.64)	(0.42)	(−4.03)	(1.64)	(2.50)	(1.31)	(−2.18)	
0.75	−0.0379	−0.00656	−0.0270	0.598***	0.281**	−0.0695	0.0614	−0.602***	−0.0798	0.187	−0.0924	0.136	0.0804
	(−0.68)	(−0.12)	(−0.49)	(5.62)	(2.61)	(−0.65)	(0.59)	(−5.49)	(−0.69)	(1.63)	(−0.78)	(0.22)	
0.8	−0.0384	0.0461	0.00147	0.753***	0.297**	−0.0132	−0.0892	−0.735***	−0.109	0.211	−0.0535	0.590	0.1005
	(−0.70)	(0.85)	(0.03)	(7.22)	(2.82)	(−0.13)	(−0.00)	(−6.85)	(−0.96)	(1.87)	(−0.46)	(0.97)	
0.85	−0.0415	0.0716	−0.0206	0.857***	0.502***	−0.0689	−0.0519	−0.713***	−0.155	0.260	−0.0566	1.447	0.1317
	(−0.62)	(1.07)	(−0.31)	(6.69)	(3.87)	(−0.54)	(−0.42)	(−5.41)	(−1.11)	(1.88)	(−0.40)	(1.94)	
0.9	−0.111	0.0676	−0.0186	0.922***	0.488**	−0.143	−0.0589	−1.042***	−0.120	0.344*	−0.0336	2.558**	0.1757
	(−1.36)	(0.84)	(−0.23)	(5.95)	(3.12)	(−0.92)	(−0.39)	(−6.54)	(−0.71)	(2.05)	(−0.19)	(2.83)	
0.95	−0.117	0.0647	−0.150	0.912***	0.690**	−0.0970	0.290	−1.789***	−0.0582	0.519*	−0.393	2.592*	0.2877
	(−1.04)	(0.58)	(−1.35)	(4.26)	(3.18)	(−0.45)	(1.39)	(−8.12)	(−0.25)	(2.24)	(−1.64)	(2.07)	
OLS	−0.132**	−0.0377	−0.0168	0.455*	0.150	−0.0923	0.0248	−0.665*	0.117	0.307**	0.0642	−1.237	0.1449
	(−3.19)	(−0.85)	(−0.34)	(2.54)	(1.67)	(−0.85)	(0.31)	(−2.53)	(0.98)	(3.20)	(0.46)	(−1.91)	

We provide the results from the lower to upper (i.e., 0.05 to 0.95) quantile regressions and the OLS regression of the changes of *ETHVOL* on the set of the independent variables. The variables $\Delta EVOL_{t-1}$, $\Delta EVOL_{t-2}$ and $\Delta EVOL_{t-3}$ represent the lags of the changes of *BITVOL*. The positive return of Ethereum is denoted by R_t^+, while the negative return of this crypto is denoted by R_t^-. Note that R_{t-1}^+, R_{t-2}^+ and R_{t-3}^+ are the lags of the positive return, while R_{t-1}^-, R_{t-2}^- and R_{t-3}^- are the lags of the negative return. The significance levels at 1%, 5% and 10% are denoted by ***, ** and *, respectively. *The t*-statistics are given in parentheses.

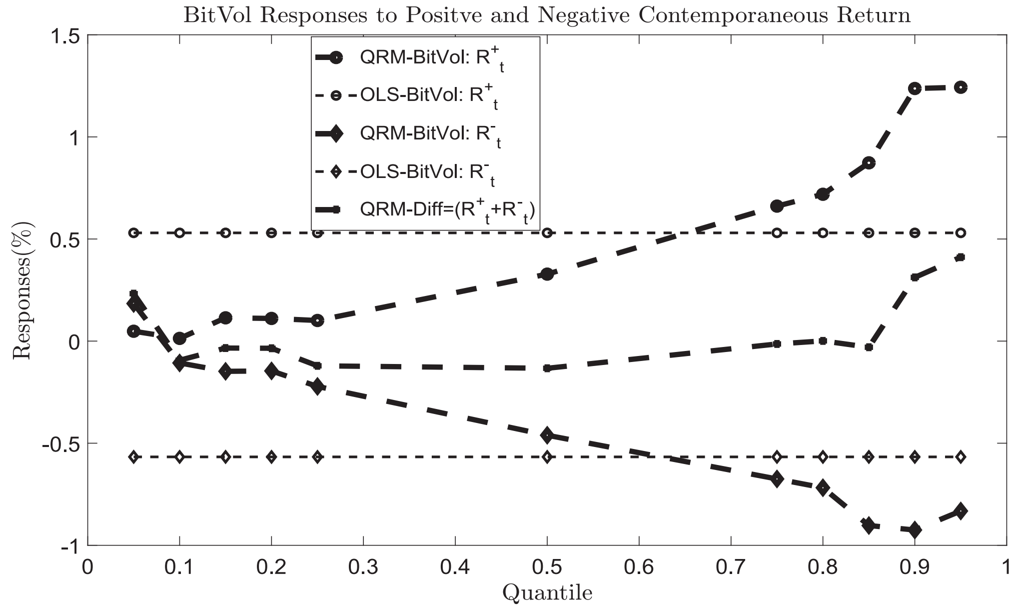

Fig. 5. *BitVol* response to contemporaneous positive and negative returns.

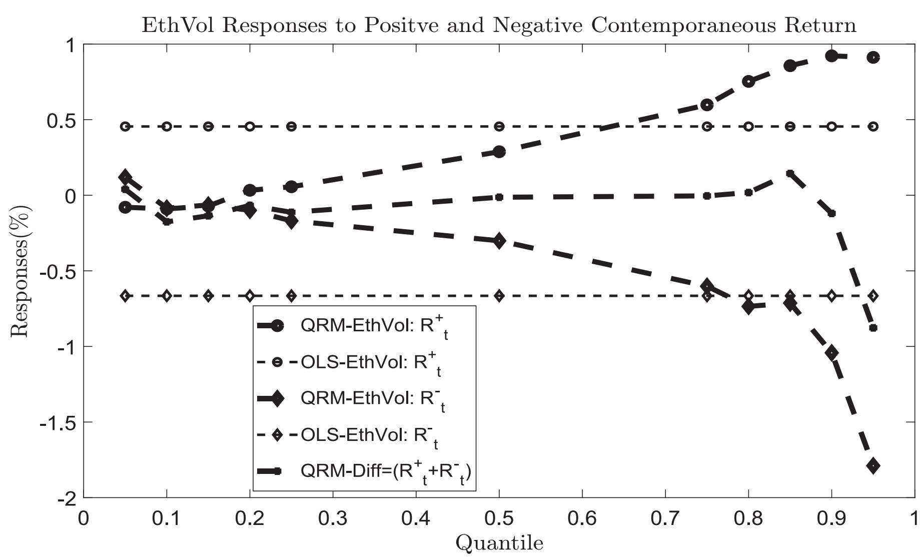

Fig. 6. *EthVol* response to contemporaneous positive and negative returns.

and R_t^-) on the changes of volatility. Fig. 4 (5) shows the impact of the cotemporaneous positive and negative return of Bitcoin (Ethereum) on the changes of Bitcoin's (Ethereum's) volatility across the quantiles ($q =$ 0. 05 to 0.95) – the lower to high volatility regimes. In Figs. 5 and 6, the upward (downward) sloping dashed-line with a circle-marked (dashed-line with diamond-marked) represents the coefficients of the cotemporaneous positive returns (negative returns). The differences of the impact of positive and negative return is presented with the dashed-lined with a small circle-shaped. It is clear that the degree of asymmetry is increasing as we move from the medium to the uppermost quantiles. However, the asymmetry is absent during the lower to the medium volatility regimes as the coefficients are not significant, which we have already discussed. There is less asymmetry at the medium quantiles of the volatility distributions (during the relatively calm periods). During high volatility regimes (an extreme tail of the volatility distribution), the degree of asymmetry seems to be very high. For Ethereum (Fig. 5), the impact of negative returns is much higher compared to the impact of positive returns – denoted by the downward dashed line with the diamond shaped marker. In contrast, for Bitcoin (Fig. 4), the impact of the positive return is much higher compared to the impact of negative return – denoted by the upward dashed line with the circle shaped marker.

5.2. Findings using NARDL

The results discussed above are estimated using the return series of the cryptocurrency and implied volatility. For that, we have calculated the percentage continuous compounding return of Bitcoin and Ethereum. Moreover, the percentage changes are measured for *BitVol* and *EthVol*. As can see from Table-1, both measures are stationary and represent short-run information. Since the difference form of the data is used, instead of using the price data (the level form), the long-term information is distorted.

Hence, besides the short-run asymmetry, to investigate the long-run asymmetry between cryptocurrency price and implied volatility's level, we have deployed the Nonlinear Autoregressive Distributive lag (NARDL). The advantage of NARDL is that it can estimate short- and long-run asymmetry at the same time within a single equation. Before applying the NARDL, we have checked if there are any I(2) variables since this approach only takes I(0) and I(1) variables. Our data satisfies this pre-condition.

We present the estimated results from the NARDL in Table 4. The number of lags is selected based on the AIC and SBIC criteria. First, we test for the presence of cointegration using the test statistics F_{PSS} and t_{BDM}. Based on the result given at the bottom of Table 4, we reject the null hypothesis of no cointegration for Bitcoin-*BitVol* and Ethereum-*EthVol*. Hence, this result supports *Hypothesis 4.1*, which claims that there is an asymmetric cointegration between cryptocurrency (i.e., Bitcoin and Ethereum) prices and the levels of implied volatility. The long- and short-run asymmetry test results are also reported at the bottom of Table 4. The test statistics of the Wald F test reject the null hypothesis of a long-run symmetry and a short-run symmetry. This result confirms that the relationship between Bitcoin (Ethereum) and *BitVol* (*EthVol*) are asymmetric in both the short- and long run. This finding also supports the *Hypothesis 4*, which says that the relationship between the cryptocurrency price and implied volatility exhibits an asymmetry in the long run.

Table 4
Testing the asymmetry of Ethereum and Bitcoin-volatility.

Variable	LETHVOL	Variable	**LBTCVOL**
$LETHVOL_{t-1}$	−0.0841*** (−4.79)	$LBTCVOL_{t-1}$	−0.0982*** (−4.74)
$LETH^{+}_{t-1}$	0.0466** (−2.74)	$LBTC^{+}_{t-1}$	0.0487** (−2.68)
$LETH^{-}_{t-1}$	0.0646* (−2.58)	$LBTC^{-}_{t-1}$	0.0729* (−2.57)
$\Delta LETHVOL_{t-1}$	−0.135** (−2.69)	$\Delta LBTCVOL_{t-1}$	−0.164** (−3.24)
$\Delta LETHVOL_{t-2}$	−0.0474 (−0.92)	$\Delta LBTCVOL_{t-2}$	−0.00802 (−0.15)
$\Delta LETHVOL_{t-3}$	−0.0346 (−0.68)	$\Delta LBTCVOL_{t-3}$	−0.0919 (−1.82)
$\Delta LETH^{+}_{t}$	0.517*** (−5.36)	$\Delta LBTC^{+}_{t}$	0.603*** (−4.8)
$\Delta LETH^{+}_{t-1}$	0.271** (−2.73)	$\Delta LBTC^{+}_{t-1}$	0.536*** (−4.22)
$\Delta LETH^{+}_{t-2}$	−0.0209 (−0.19)	$\Delta LBTC^{+}_{t-2}$	0.536*** (−4.22)
$\Delta LETH^{+}_{t-3}$	0.212* (−1.98)	$\Delta LBTC^{+}_{t-3}$	0.162 (−1.2)
$\Delta LETH^{-}_{t}$	−0.655*** (−6.28)	$\Delta LBTC^{-}_{t}$	−0.885*** (−6.77)
$\Delta LETH^{-}_{t-1}$	0.0773 (−0.68)	$\Delta LBTC^{-}_{t-1}$	−0.197 (−1.31)
$\Delta LETH^{-}_{t-2}$	0.208 (−1.81)	$\Delta LBTC^{-}_{t-2}$	0.0525 (−0.35)
$\Delta LETH^{-}_{t-3}$	−0.182 (−1.55)	$\Delta LBTC^{-}_{t-3}$	−0.0213 (−0.14)
Intercept	0.339*** (−4.59)	*Intercept*	−0.394*** (−4.59)
Long run asymmetry		*Long run asymmetry*	
$LETH^{+}_{t}$	0.554***	$LBTC^{+}_{t}$	0.496***
$LETH^{-}_{t}$	−0.770***	$LBTC^{-}_{t}$	−0.742***
W_{LR}	5.486***	W_{LR}	8.286***
Short run asymmetry		*Short run asymmetry*	
W_{SR}	22.14***	W_{SR}	24.78***
Cointegration test		*Cointegration test*	
F_{PSS}	7.7165***	F_{PSS}	7.7308***
T_{BDM}	−4.7912***	T_{BDM}	−4.7395***

We provide the findings derived by using the Non-linear ARDL estimation. Dependent variables LETHVOL and LBTCVOL refer to the log of *ETHVOL* and *BTCVOL*, respectively. is the Wald test for the long-run asymmetry and is the Wald test for the short-run asymmetry. The non-linear cointegration is tested using the test statistics and. Note that, and are the asymmetric positive and negative long-run coefficients. Additionally, and are the asymmetric positive and negative short-run contemporaneous coefficients. The significance levels at 1%, 5% and 10% are denoted by ***, ** and *, respectively. The standard errors are given in parenthesis.

The long-run coefficients of the increase and decrease in the Bitcoin (Ethereum) price are 0.496 (0.554) and − 0.742 (−0.770), respectively, and significant at the 1% level. It means that the Bitcoin (Ethereum) price increases and decreases lead to an increase in the implied volatility of the Bitcoin and Ethereum (*BitVol* and *EthVol*). This finding rejects *Hypothesis 4.2,* which claims that the implied volatility and the cryptocurrency price are negatively co-related. Moreover, the impact of the negative price movement of Bitcoin (Ethereum) on the positive innovation of *BitVol* (*EthVol*) is much higher compared to the impact of the positive price movement of Bitcoin (Ethereum) on the positive innovation of *BitVol* (*EthVol*). For example, a 1 percentage point increase (decrease) in the Bitcoin price is associated with a 0.496 (0.742) percentage point increase in *BITVOL*. It implies that in the long run, for both Bitcoin and Ethereum, excess buyer-motivated trade is much higher following the bad news compared to the excess buyer-motivated trade following the good news. This finding support *Hypothesis 4.3,* which claims that the negative price movement has a greater impact on implied volatility compared to the positive price movement.

For the short run, as can be seen in Table 4, the contemporaneous coefficients of the positive and negative changes of Bitcoin return ($\Delta LBTC^{+}_{t}$ and$\Delta LBTC^{-}_{t}$) are 0.603 and − 0.885 and, for Ethereum, ($\Delta LETH^{+}_{t}$ and$\Delta LETH^{-}_{t}$) are 0.517 and − 0.655, respectively, and significant at the 1% level. It means, the same as for the long-run, the positive innovation of *BitVol* and *EthVol* are more associated with the negative return-shocks. Moreover, results also confirm that that the positive and negative return-shocks of cryptocurrency (Bitcoin and Ethereum) are linked to the increase in the implied volatility (*BitVol* and *EthVol).* the impact of lags retunes are mostly insignificant after one lag, the same as the finding from QRM.

We provide the findings derived by using the Non-linear ARDL estimation. Dependent variables LETHVOL and LBTCVOL refer to the log of *ETHVOL* and *BTCVOL*, respectively. W_{LR} is the Wald test for the long-run asymmetry and W_{SR} is the Wald test for the short-run asymmetry. The non-linear cointegration is tested using the test statistics F_{PSS} and t_{BDM}. Note that $LBTC^{+}_{t}$ $LBTC^{-}_{t}$, $LETH^{+}_{t}$ and $LETH^{-}_{t}$ are the asymmetric positive and negative long-run coefficients. Additionally, $\Delta LBTC^{+}_{t}$ $\Delta LBTC^{-}_{t}$, $\Delta LETH^{+}_{t}$ and $\Delta LETH^{-}_{t}$ are the asymmetric positive and negative short-run contemporaneous coefficients. The significance levels at 1%, 5% and 10% are denoted by ***, ** and *, respectively. The standard errors are given in parenthesis.

The asymmetric cumulative dynamic multipliers for both Bitcoin and Ethereum are displayed in Figs. 7 and 8. It shows that the temporal evolution of *BitVol* (Fig. 7) and *EthVol* (Fig. 8) in response to the increase and decrease of the Bitcoin and Ethereum over the 80-day horizons. The green dashed curve (the red dashed curve) represents the response to positive (negative) changes. The confidence interval (at the 90% level) is shown in the grey-color shaded area. The solid blue curve, together with the confidence interval, shows the difference in the upward and downward movements. It is clearly shown that in the long run, the impact of the negative price movement on increasing the positive innovation in the volatility is much higher than the impact of the positive price movement on the increase of the positive innovation in the volatility.

6. Discussion

Cryptocurrencies, characterized by their controversial nature as mediums of exchange and stores of value, are known for their inherent volatility (Hazlett & Luther, 2020; Levulytė & Šapkauskienė, 2021; Yermack, 2015). This volatility is further compounded by the absence of underlying assets, leaving investors uncertain about the appropriate valuation. However, there are potential avenues for reducing

Table 5
Robustness testing the changes of Ethereum volatility across the quantiles (using first half of the sample data).

Quantile	$\Delta EVOL_{t-1}$	$\Delta EVOL_{t-2}$	$\Delta EVOL_{t-3}$	R_t^+	R_{t-1}^+	R_{t-2}^+	R_{t-3}^+	R_t^-	R_{t-1}^-	R_{t-2}^-	R_{t-3}^-	Intercept	R^2
0.05	−0.0568	−0.0574	−0.000316	0.0188	−0.0329	−0.188	0.138	0.408	−0.127	0.252	−0.277	−7.153***	0.1097
	(−0.40)	(−0.40)	(−0.00)	(0.07)	(−0.12)	(−0.67)	(0.51)	(1.33)	(−0.40)	(0.80)	(−0.86)	(−4.42)	
0.1	−0.0742	−0.0888	−0.0156	0.0658	0.0545	−0.214	0.164	0.399*	0.0434	0.183	−0.243	−5.904***	0.0698
	(−0.84)	(−1.01)	(−0.18)	(0.41)	(0.31)	(−1.23)	(0.97)	(2.10)	(0.22)	(0.93)	(−1.22)	(−5.88)	
0.15	−0.156	−0.0517	−0.0241	0.0244	0.188	−0.132	0.0832	0.171	−0.0589	0.214	−0.0238	−4.466***	0.0559
	(−1.80)	(−0.60)	(−0.28)	(0.15)	(1.10)	(−0.77)	(0.50)	(0.92)	(−0.31)	(1.12)	(−0.12)	(−4.54)	
0.2	−0.180*	−0.0413	0.0179	0.0593	0.318*	−0.144	−0.0258	0.147	−0.0453	0.284	0.0772	−3.449***	0.0529
	(−2.53)	(−0.58)	(0.25)	(0.45)	(2.28)	(−1.03)	(−0.19)	(0.96)	(−0.29)	(1.80)	(0.48)	(−4.27)	
0.25	−0.208***	−0.0535	0.0209	0.141	0.318**	−0.134	0.0249	0.0153	0.0237	0.302**	0.138	−3.257***	0.0525
	(−3.95)	(−1.02)	(0.40)	(1.46)	(3.09)	(−1.30)	(0.25)	(0.14)	(0.20)	(2.60)	(1.17)	(−5.47)	
Median	−0.108	−0.0731	−0.0152	0.491***	0.244	−0.0671	0.0302	−0.139	0.192	0.393*	0.122	−0.838	0.0597
	(−1.57)	(−1.07)	(−0.22)	(3.89)	(1.81)	(−0.50)	(0.23)	(−0.94)	(1.26)	(2.59)	(0.79)	(−1.07)	
0.75	−0.0606	−0.0122	0.00343	0.980***	0.519***	−0.248	−0.0277	−0.747***	−0.139	0.384*	−0.143	0.229	0.1313
	(−0.84)	(−0.17)	(0.05)	(7.45)	(3.69)	(−1.76)	(−0.20)	(−4.86)	(−0.88)	(2.42)	(−0.89)	(0.28)	
0.8	−0.0612	0.0224	0.00782	0.967***	0.763***	−0.131	−0.0814	−0.741***	−0.115	0.441**	−0.0891	0.849	0.166
	(−0.80)	(0.29)	(0.10)	(6.86)	(5.06)	(−0.87)	(−0.56)	(−4.50)	(−0.68)	(2.60)	(−0.51)	(0.97)	
0.85	−0.0807	0.0510	−0.0409	0.954***	0.723***	−0.185	0.0252	−0.743***	−0.0259	0.466**	−0.158	1.741*	0.2071
	(−1.18)	(0.75)	(−0.61)	(7.61)	(5.40)	(−1.38)	(0.19)	(−5.07)	(−0.17)	(3.09)	(−1.02)	(2.25)	
0.9	−0.164	0.00962	−0.0711	0.950***	0.675*	−0.00938	0.102	−0.722*	−0.0635	0.411	−0.0653	2.327	0.2558
	(−1.12)	(0.07)	(−0.49)	(3.55)	(2.37)	(−0.03)	(0.37)	(−2.31)	(−0.20)	(1.28)	(−0.20)	(1.41)	
0.95	−0.127	−0.0416	−0.199	1.265***	1.089**	−0.232	0.589	−1.406**	0.140	0.604	−0.856	2.213	0.3254
	(−0.62)	(−0.21)	(−0.99)	(3.39)	(2.73)	(−0.58)	(1.52)	(−3.22)	(0.31)	(1.34)	(−1.87)	(0.96)	
OLS	−0.138*	0.00575	−0.0165	0.694***	0.315	−0.140	−0.00650	−0.330	0.0595	0.382**	0.0117	−1.377*	0.1649
	(−2.50)	(0.11)	(−0.30)	(4.22)	(1.90)	(−0.95)	(−0.07)	(−1.68)	(0.41)	(2.94)	(0.09)	(−2.28)	

We provide the results from the lower to upper (i.e., 0.05 to 0.95) quantile regressions and the OLS regression of the changes of *ETHVOL* on the set of the independent variables. The variables $\Delta EVOL_{t-1}$, $\Delta EVOL_{t-2}$ and $\Delta EVOL_{t-3}$ represent the lags of the changes of *BITVOL*. The positive return of Ethereum is denoted by R_t^+, while the negative return of this crypto is denoted by R_t^-. Note that R_{t-1}^+, R_{t-2}^+ and R_{t-3}^+ are the lags of the positive return, while R_{t-1}^-, R_{t-2}^- and R_{t-3}^- are the lags of the negative return. The significance levels at 1%, 5% and 10% are denoted by ***, ** and *, respectively. *The t*-statistics are given in parentheses.

Table 6
Robustness testing the changes of Ethereum volatility across the quantiles (using the last half of the sample data).

Quantile	$\Delta EVOL_{t-1}$	$\Delta EVOL_{t-2}$	$\Delta EVOL_{t-3}$	R_t^+	R_{t-1}^+	R_{t-2}^+	R_{t-3}^+	R_t^-	R_{t-1}^-	R_{t-2}^-	R_{t-3}^-	Intercept	R^2
0.05	−0.265	−0.235	−0.0376	−0.207	−0.0905	0.0393	−0.0664	−0.239	0.0372	−0.235	0.130	−6.068***	0.2079
	(−1.75)	(−1.54)	(−0.25)	(−0.71)	(−0.33)	(0.14)	(−0.25)	(−0.93)	(0.13)	(−0.85)	(0.44)	(−3.98)	
0.1	−0.195**	−0.214**	−0.130	−0.0112	−0.0350	−0.0548	−0.193	−0.388**	0.0632	−0.176	0.313*	−4.498***	0.1504
	(−2.71)	(−2.96)	(−1.81)	(−0.08)	(−0.27)	(−0.43)	(−1.54)	(−3.18)	(0.47)	(−1.34)	(2.21)	(−6.23)	
0.15	−0.190***	−0.182**	−0.0751	0.0400	−0.164	0.0185	−0.131	−0.334***	0.0580	−0.152	0.272*	−3.835***	0.1092
	(−3.39)	(−3.22)	(−1.34)	(0.37)	(−1.61)	(0.18)	(−1.34)	(−3.51)	(0.55)	(−1.48)	(2.46)	(−6.80)	
0.2	−0.145**	−0.160**	−0.141**	0.0407	−0.269**	0.0163	−0.0607	−0.362***	0.190	−0.0885	0.169	−2.954***	0.0923
	(−2.80)	(−3.08)	(−2.72)	(0.41)	(−2.86)	(0.18)	(−0.67)	(−4.12)	(1.96)	(−0.93)	(1.66)	(−5.68)	
0.25	−0.144*	−0.124*	−0.0979	0.0581	−0.256*	0.0486	0.0403	−0.302**	0.223*	−0.0310	0.136	−2.505***	0.0805
	(−2.53)	(−2.16)	(−1.71)	(0.53)	(−2.47)	(0.48)	(0.40)	(−3.12)	(2.09)	(−0.30)	(1.21)	(−4.37)	
Median	−0.132*	−0.0870	−0.107*	0.0954	0.0161	−0.00448	0.101	−0.279**	0.137	0.137	0.0927	−0.730	0.0655
	(−2.44)	(−1.60)	(−1.97)	(0.92)	(0.16)	(−0.05)	(1.07)	(−3.04)	(1.35)	(1.38)	(0.87)	(−1.34)	
0.75	−0.0394	−0.00538	0.00300	0.370***	−0.0252	0.0933	0.0508	−0.652***	0.0736	0.170	0.0651	0.762	0.0926
	(−0.70)	(−0.10)	(0.05)	(3.44)	(−0.25)	(0.93)	(0.52)	(−6.85)	(0.70)	(1.65)	(0.59)	(1.35)	
0.8	−0.0141	−0.000418	0.0314	0.326*	−0.0163	0.121	0.0463	−0.683***	0.0189	0.184	−0.0775	0.970	0.1032
	(−0.18)	(−0.01)	(0.40)	(2.17)	(−0.11)	(0.86)	(0.34)	(−5.12)	(0.13)	(1.27)	(−0.50)	(1.23)	
0.85	0.0158	0.0860	−0.00559	0.345	0.0830	0.0859	−0.0513	−0.760***	−0.0487	0.257	−0.163	1.517	0.1099
	(0.13)	(0.69)	(−0.05)	(1.46)	(0.37)	(0.39)	(−0.24)	(−3.62)	(−0.21)	(1.13)	(−0.67)	(1.22)	
0.9	−0.0735	0.210	−0.0506	0.510	0.240	−0.0333	0.114	−1.259***	−0.186	0.377	−0.238	1.676	0.1451
	(−0.42)	(1.18)	(−0.29)	(1.50)	(0.74)	(−0.11)	(0.37)	(−4.19)	(−0.56)	(1.16)	(−0.68)	(0.94)	
0.95	0.0428	0.247	−0.177	0.632*	0.307	−0.120	0.268	−2.013***	0.0565	0.177	−0.738*	2.258	0.2845
	(0.29)	(1.68)	(−1.21)	(2.26)	(1.16)	(−0.46)	(1.05)	(−8.11)	(0.21)	(0.66)	(−2.56)	(1.54)	
OLS	−0.148*	−0.0914	−0.00113	0.121	−0.0471	−0.123	0.0576	−0.865*	0.143	0.236	0.0210	−0.810	0.2635
	(−2.57)	(−1.29)	(−0.01)	(0.62)	(−0.46)	(−1.20)	(0.47)	(−2.29)	(0.99)	(1.59)	(0.12)	(−0.98)	

We provide the results from the lower to upper (i.e., 0.05 to 0.95) quantile regressions and the OLS regression of the changes of *ETHVOL* on the set of the independent variables. The variables, and represent the lags of the changes of *BITVOL*. The positive return of Ethereum is denoted by while the negative return of this crypto is denoted by. Note that, and are the lags of the positive return, while, and are the lags of the negative return. The significance levels at 1%, 5% and 10% are denoted by ***, ** and *, respectively. The t-statistics are given in parentheses.

Table 7
Robustness testing the changes of Bitcoin volatility across the quantiles (using first half of the sample data).

Quantile	$\Delta BVOL_{t-1}$	$\Delta BVOL_{t-2}$	$\Delta BVOL_{t-3}$	R_t^+	R_{t-1}^+	R_{t-2}^+	R_{t-3}^+	R_t^-	R_{t-1}^-	R_{t-2}^-	R_{t-3}^-	Intercept	R^2
0.05	−0.305**	0.0128	0.0263	0.0478	0.292	0.0135	−0.389	0.0797	−0.517	0.283	0.253	−8.086***	0.1031
	(−2.89)	(0.12)	(0.26)	(0.17)	(1.02)	(0.05)	(−1.32)	(0.28)	(−1.78)	(0.94)	(0.84)	(−6.14)	
0.1	−0.144*	0.0333	0.00419	−0.0791	0.234	−0.0507	−0.361	0.378	−0.407*	0.231	0.129	−5.451***	0.0692
	(−2.02)	(0.47)	(0.06)	(−0.42)	(1.20)	(−0.25)	(−1.81)	(1.93)	(−2.07)	(1.14)	(0.63)	(−6.12)	
0.15	−0.135*	0.0693	−0.0168	0.149	0.155	−0.0930	−0.284	0.0578	−0.313	0.191	0.310	−4.479***	0.0484
	(−2.19)	(1.13)	(−0.29)	(0.91)	(0.93)	(−0.54)	(−1.65)	(0.34)	(−1.86)	(1.10)	(1.76)	(−5.85)	
0.2	−0.0931*	0.0400	−0.0302	0.241*	0.112	−0.189	−0.159	−0.173	−0.223	0.0340	0.351**	−3.654***	0.0488
	(−2.05)	(0.89)	(−0.70)	(2.00)	(0.91)	(−1.49)	(−1.26)	(−1.39)	(−1.79)	(0.26)	(2.70)	(−6.46)	
0.25	−0.0775	0.0249	−0.0380	0.280*	0.0974	−0.124	−0.159	−0.143	−0.231*	−0.0443	0.374**	−3.325***	0.0466
	(−1.89)	(0.61)	(−0.98)	(2.58)	(0.88)	(−1.08)	(−1.39)	(−1.27)	(−2.05)	(−0.38)	(3.19)	(−6.51)	
Median	−0.0990**	−0.0266	−0.0585	0.550***	0.325***	−0.0110	−0.225*	−0.507***	−0.488***	−0.0318	0.318**	−2.027***	0.0671
	(−2.84)	(−0.77)	(−1.78)	(5.94)	(3.44)	(−0.11)	(−2.32)	(−5.33)	(−5.11)	(−0.32)	(3.19)	(−4.67)	
0.75	−0.0737	−0.0613	−0.116*	0.656***	0.875***	−0.0931	−0.215	−0.492**	−0.386*	−0.0734	0.140	0.146	0.1318
	(−1.26)	(−1.06)	(−2.10)	(4.23)	(5.52)	(−0.57)	(−1.32)	(−3.08)	(−2.41)	(−0.44)	(0.84)	(0.20)	
0.8	−0.0904	−0.0198	−0.147*	0.809***	1.250***	−0.110	−0.244	−0.486**	−0.796***	−0.198	0.307	0.336	0.1534
	(−1.32)	(−0.29)	(−2.27)	(4.44)	(6.72)	(−0.58)	(−1.27)	(−2.59)	(−4.23)	(−1.02)	(1.56)	(0.39)	
0.85	−0.0443	−0.0425	−0.145	1.059***	1.244***	−0.211	−0.267	−0.766***	−0.876***	−0.156	0.253	0.613	0.1857
	(−0.55)	(−0.53)	(−1.89)	(4.92)	(5.65)	(−0.93)	(−1.18)	(−3.45)	(−3.94)	(−0.68)	(1.09)	(0.61)	
0.9	−0.0669	−0.0574	−0.140	1.260***	1.279***	−0.231	−0.245	−1.072**	−0.664	−0.942*	0.243	1.187	0.2265
	(−0.50)	(−0.43)	(−1.11)	(3.56)	(3.54)	(−0.62)	(−0.66)	(−2.95)	(−1.82)	(−2.50)	(0.64)	(0.72)	
0.95	−0.0637	−0.136	−0.0654	2.172***	2.067***	−0.383	0.159	−0.950**	−2.190***	−0.795*	−0.148	1.069	0.3488
	(−0.48)	(−1.02)	(−0.52)	(6.11)	(5.69)	(−1.03)	(0.43)	(−2.60)	(−5.96)	(−2.10)	(−0.39)	(0.64)	
OLS	−0.0481	0.0109	−0.0990*	0.762***	0.716**	−0.194	−0.402**	−0.529**	−0.964*	−0.136	0.421*	−2.573**	0.2332
	(−0.50)	(0.23)	(−2.28)	(3.48)	(2.59)	(−1.67)	(−2.64)	(−3.30)	(−2.01)	(−0.46)	(2.51)	(−3.24)	

Notes. We provide findings from the lower to upper (i.e., 0.05 to 0.95) quantile regressions and the OLS regression of the changes of *BITVOL* on the set of independent variables. $\Delta BVOL_{t-1}$, $\Delta BVOL_{t-2}$ and $\Delta BVOL_{t-3}$ represent the lags of the changes of *BITVOL*. The positive return of the Bitcoin is denoted by R_t^+ while the negative return of this crypto currency is denoted by R_t^-. Note that R_{t-1}^+, R_{t-2}^+ and R_{t-3}^+ are the lags of the positive returns. R_{t-1}^-, R_{t-2}^- and R_{t-3}^- are the lags of the negative returns. The significance levels at 1%, 5% and 10% are denoted by ***, ** and *, respectively. The t-statistics are given in parentheses.

Table 8
Robustness testing the changes of Bitcoin volatility across the quantiles (using the last half of the sample data).

Quantile	$\Delta BVOL_{t-1}$	$\Delta BVOL_{t-2}$	$\Delta BVOL_{t-3}$	R_t^+	R_{t-1}^+	R_{t-2}^+	R_{t-3}^+	R_t^-	R_{t-1}^-	R_{t-2}^-	R_{t-3}^-	Intercept	R^2
0.05	−0.169	−0.121	−0.0801	−0.191	0.175	−0.529	−0.0692	−0.153	0.0930	0.180	0.0249	−4.841***	0.1723
	(−1.22)	(−0.87)	(−0.58)	(−0.66)	(0.61)	(−1.83)	(−0.25)	(−0.54)	(0.31)	(0.60)	(0.08)	(−3.50)	
0.1	−0.166**	−0.105	−0.125*	−0.206	−0.000297	−0.365**	0.219	−0.155	0.171	0.128	0.0435	−3.875***	0.1439
	(−2.79)	(−1.75)	(−2.12)	(−1.67)	(−0.00)	(−2.94)	(1.81)	(−1.27)	(1.33)	(1.00)	(0.34)	(−6.51)	
0.15	−0.185**	−0.142*	−0.110	−0.0581	−0.00769	−0.345**	0.173	−0.118	0.236	0.164	0.131	−2.949***	0.1105
	(−3.10)	(−2.36)	(−1.85)	(−0.47)	(−0.06)	(−2.77)	(1.43)	(−0.96)	(1.82)	(1.27)	(1.01)	(−4.94)	
0.2	−0.178***	−0.0635	−0.145**	−0.0427	−0.0694	−0.173	0.169	−0.0722	0.176	0.197	0.121	−2.232***	0.0913
	(−3.36)	(−1.19)	(−2.76)	(−0.39)	(−0.63)	(−1.57)	(1.57)	(−0.66)	(1.53)	(1.72)	(1.05)	(−4.21)	
0.25	−0.152***	−0.0570	−0.111*	0.00611	−0.00348	−0.219*	0.0877	−0.299***	0.188*	0.279**	0.146	−1.796***	0.0845
	(−3.49)	(−1.30)	(−2.56)	(0.07)	(−0.04)	(−2.42)	(0.99)	(−3.33)	(2.00)	(2.96)	(1.54)	(−4.12)	
Median	−0.117*	−0.0413	−0.116*	0.168	0.0793	−0.252*	−0.0117	−0.495***	0.0160	0.299**	0.120	−0.299	0.076
	(−2.48)	(−0.87)	(−2.48)	(1.71)	(0.81)	(−2.57)	(−0.12)	(−5.11)	(0.16)	(2.94)	(1.17)	(−0.63)	
0.75	−0.116	−0.0119	−0.0413	0.488***	0.382**	−0.147	−0.0188	−0.733***	−0.165	0.225	0.196	0.684	0.0966
	(−1.79)	(−0.18)	(−0.64)	(3.61)	(2.82)	(−1.08)	(−0.14)	(−5.49)	(−1.17)	(1.61)	(1.39)	(1.05)	
0.8	−0.149*	−0.0362	−0.122	0.641***	0.505***	−0.0905	0.0415	−0.908***	−0.160	0.167	0.0900	0.466	0.109
	(−2.12)	(−0.51)	(−1.75)	(4.40)	(3.47)	(−0.62)	(0.29)	(−6.31)	(−1.05)	(1.11)	(0.59)	(0.67)	
0.85	−0.0990	−0.0179	−0.158	0.741***	0.409*	0.0152	0.0260	−0.967***	−0.300	0.0201	0.115	0.843	0.1245
	(−1.14)	(−0.21)	(−1.84)	(4.11)	(2.27)	(0.08)	(0.15)	(−5.43)	(−1.60)	(0.11)	(0.61)	(0.97)	
0.9	−0.0535	0.0233	−0.110	1.131***	0.370	0.0548	0.187	−0.912***	−0.236	−0.121	0.0496	1.159	0.1531
	(−0.47)	(0.20)	(−0.97)	(4.77)	(1.56)	(0.23)	(0.81)	(−3.89)	(−0.96)	(−0.49)	(0.20)	(1.02)	
0.95	−0.0537	0.0762	0.180	1.240***	0.590	−0.132	0.0886	−1.025**	−0.621	0.155	0.229	3.399	0.2052
	(−0.31)	(0.43)	(1.03)	(3.40)	(1.61)	(−0.36)	(0.25)	(−2.84)	(−1.64)	(0.41)	(0.60)	(1.94)	
OLS	−0.169**	−0.0441	−0.132*	0.354*	0.230*	−0.136	0.00833	−0.585***	−0.0518	0.183	0.205	−0.880	0.1415
	(−2.87)	(−0.78)	(−2.34)	(2.30)	(1.99)	(−1.36)	(0.07)	(−4.20)	(−0.34)	(1.56)	(1.73)	(−1.45)	

Notes. We provide findings from the lower to upper (i.e., 0.05 to 0.95) quantile regressions and the OLS regression of the changes of *BITVOL* on the set of independent variables. $\Delta BVOL_{t-1}$, $\Delta BVOL_{t-2}$ and $\Delta BVOL_{t-3}$ represent the lags of the changes of *BITVOL*. The positive return of the Bitcoin is denoted by R_t^+ while the negative return of this crypto currency is denoted by R_t^-. Note that R_{t-1}^+, R_{t-2}^+ and R_{t-3}^+ are the lags of the positive returns. R_{t-1}^-, R_{t-2}^- and R_{t-3}^- are the lags of the negative returns. The significance levels at 1%, 5% and 10% are denoted by ***, ** and *, respectively. The t-statistics are given in parentheses.

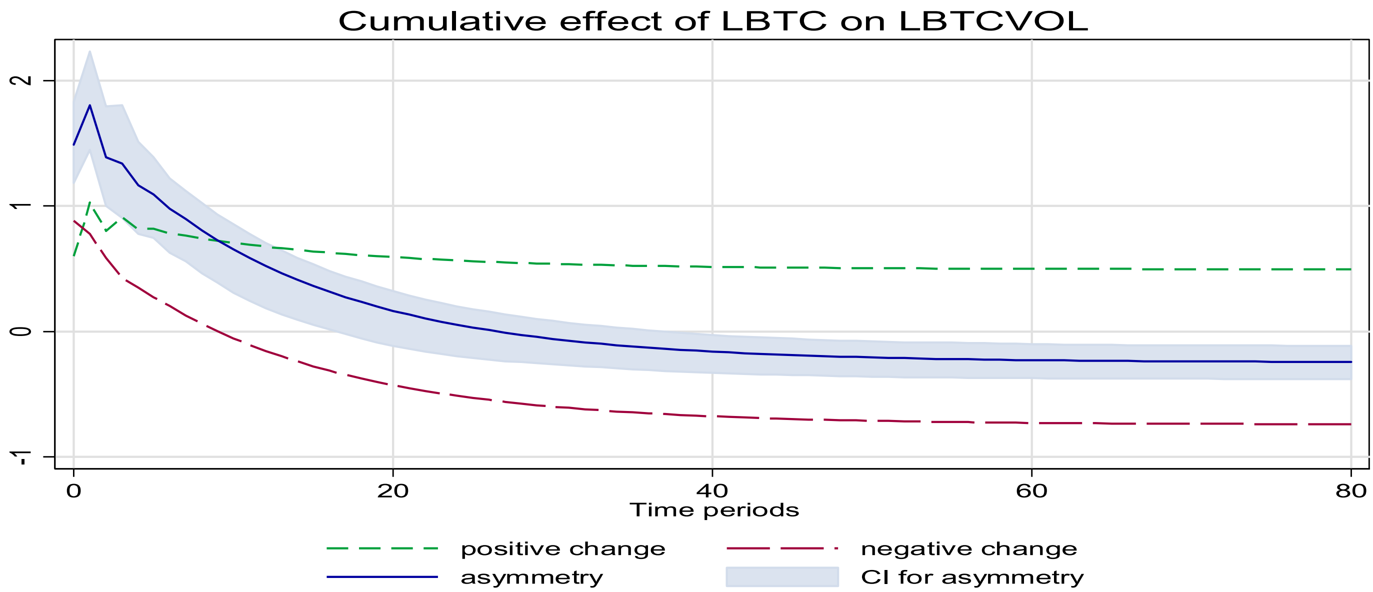

Fig. 7. Dynamic multiplier, Bitcoin.

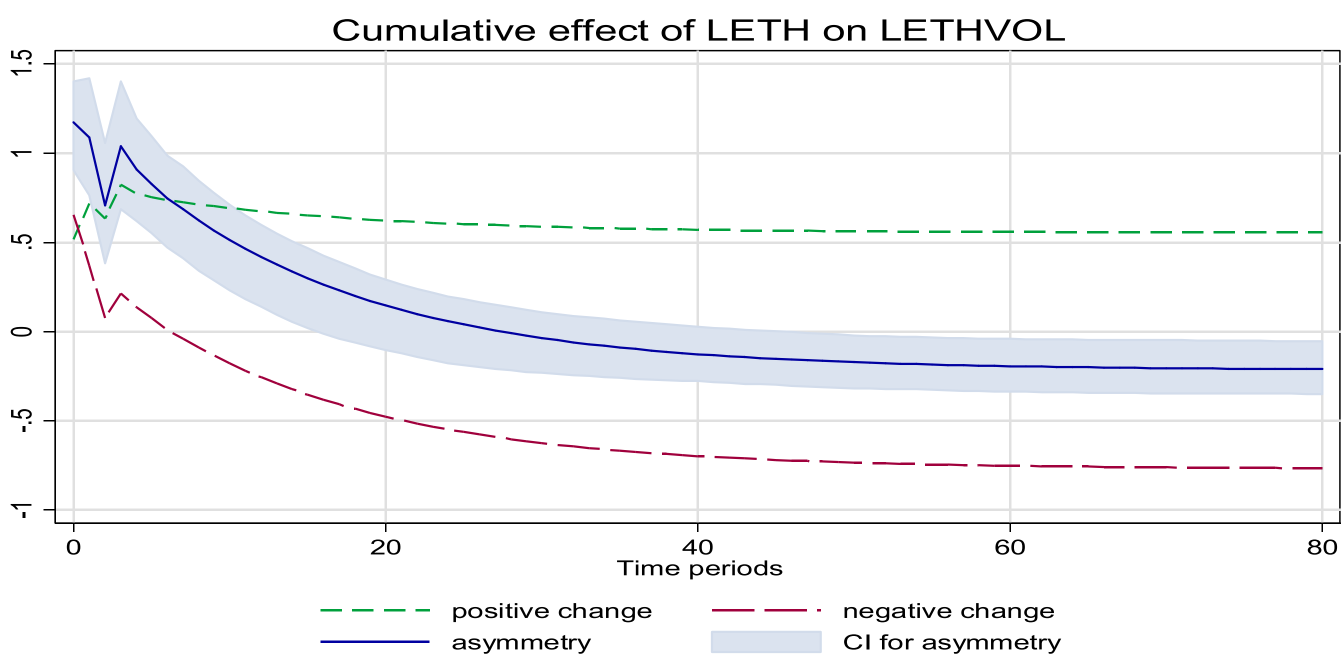

Fig. 8. Dynamic multiplier, ethereum.

cryptocurrency volatility, including the implementation of a regulatory framework, enhancing liquidity in the cryptocurrency market, and increasing the availability of trading pairs (Belke & Beretta, 2020). Furthermore, they contend that the volatility in cryptocurrencies represents a trade-off, as regulatory interventions cannot artificially support or suppress it. In addition to the aforementioned considerations and reasons, cryptocurrencies continue to exhibit volatility, and as of now, there is no study documenting whether price movements, be they positive or negative, can consistently induce volatility nearly every day. This raises the question of whether the existing factors are sufficient to fully explain cryptocurrency volatility or whether other elements, such as investors' perspectives, psychological behaviors, and market phenomena, may also play crucial roles in shaping cryptocurrency price behavior. The answer to this question remains unknown and warrants further attention from academics and experts.

The recent studies of Trucíos (2019), Shen, Urquhart, and Wang (2020) and Hoang and Baur (2020) focus on the importance of estimating risk using various forecasting methods based on the realized volatility of bitcoin. Other studies have examined the cryptocurrency price discoveries (Baur & Dimpfl, 2018) and herding behavior (Ballis & Drakos, 2020; King & Koutmos, 2021; Yarovaya et al., 2020). The above studies also provide insights on the presence of asymmetry, structural break, drastic price movement and outliers, which play a significant role in explaining the bitcoin risk. However, it is not obvious how nonlinearity and asymmetric works between the return-volatility relationship of Bitcoin and Ethereum, which is pivotal for a better investment decision for hedging, market timing, and innovative trading strategies. To the best of our knowledge, there is hardly any study examining the non-linearity and asymmetric pattern in the light of the implied volatility of Bitcoin and Ethereum. This is important as these cryptocurrencies show the highest volatility pattern out of all the financial asset classes.

To address this issue, we conduct our study using a newly constructed volatility–model-free implied volatility of Bitcoin and Ethereum- to examine the dynamic relation between daily crypto returns and daily innovations in the crypto-derived implied volatility with the application of the quantile regression and the non-linear ARDL. We find that the changes in implied volatility are directly related to the positive and negative shocks to the returns. In particular, for Bitcoin, the good news (the positive-return shock) compared to the bad news (the negative return-shock) has a greater impact on the positive innovation (increasing) of the volatility at the medium to the upper quantiles and more pronounced at the uppermost quantile (extreme-tail). In contrast, for Ethereum, it is the negative news (the negative return-shock) that increases the volatility most at the uppermost quantile. Unlike equity, for Bitcoin and Ethereum, both positive and negative return-shocks increase the volatility (*BitVol* and *EthVol*).

Moreover, using the NARDL, we also find the short- and long-run asymmetric predictive power (asymmetric volatility phenomenon) shows a negative-return shock which has a more explanatory power on the positive innovation of the volatility in the short- and long-run. Besides the foregoing reasons of volatility, we bring up the reasons of manipulation and speculation driven by the behavioral aspects in the market which are also responsible for high volatility that are captured through the return series of the cryptocurrencies. Thus, we highlight the market-wide factors such as *noise trading, behavioral/emotional biases, fear of missing out* that cause the cryptocurrency volatility. Hence, the findings of our study provide important inputs for the investors to consider when preparing or revising their investment strategies for Bitcoin in the future.

7. Conclusion

Using the newly introduced robust volatility indices, BitVol and EthVol, for Bitcoin and Ethereum, respectively, we have studied the asymmetric return-volatility relationship of these cryptocurrencies employing quantile regression and non-linear ARDL methodologies. With the quantile regression, we quantified the impact of positive and negative returns of Bitcoin and Ethereum across different quantiles (from lower to upper quantiles) of the MFIV change distribution. This analysis addresses the relationship between cryptocurrency returns and volatility, the presence of an asymmetric return-volatility relationship (positive or negative), and the extent of asymmetric responses in the uppermost quantiles compared to median (or mean) regressions.

Furthermore, utilizing non-linear ARDL, we explored the asymmetric cointegration and short- and long-run asymmetry of the variables under study. To achieve this, we used the level form of the data rather than return series. Additionally, apart from serving as a robustness check for examining the asymmetric relationship, NARDL provides us with additional new insights.

The results strongly support the presence of an asymmetric return-volatility relationship. The impact of the positive and negative returns of Bitcoin and Ethereum on the corresponding volatility indices (*BitVol* and *EthVol)* are asymmetric at the medium to upper quantiles. As we move from the medium to the uppermost quantiles, the asymmetry monotonically increases. Unlike in the case of equity, the positive innovation of the volatility (*BitVol* and *EthVol*) is linked to both positive and negative returns of the two cryptocurrencies (Bitcoin and Ethereum). This means that both positive and negative shocks in returns lead to an increase in volatility. Moreover, during the high volatility regimes, for Bitcoin (Ethereum) compared to the negative (positive) return-shock, the positive (negative) return-shock has a greater impact on the positive innovation of the volatility. The positive innovation of the volatility due to positive and negative return-shocks is more pronounced at the uppermost quantile – denoted as the high volatility regimes. We can conclude that, for Ethereum, following the bad news, the excess buyer-motivated trade is much higher during the high volatility regimes. Market participants want to gain profit by buying at lower prices. In contrast, for Bitcoin, following the good news, the excess buyer-motivated trade is much higher during the high volatility regimes. It is because, for Bitcoin, being the most popular cryptocurrency, noise trading activities are much high following a positive price movement. It is mainly due to the fear of missing out.

The NARDL estimation result also confirms the existence of short- and long-run asymmetry and cointegration. It also confirms that (both) the increase and decrease of the returns lead to an increase in volatility. It also shows that in the long run the positive innovation of the volatility is more associated with the negative price movement than with the favorable price movement. In sum, our results tend to indicate that both negative and positive returns lead to an increase in the level of volatility. However, the negative-return shocks tend to have a greater impact on the positive innovation of the volatility in both sort and long-run.

This finding may assist investors in formulating a robust trading strategy, particularly for market timing. By considering different volatility regimes, traders can make informed decisions about the right time to invest or cash out based on their position in the cryptocurrency market. Furthermore, in addition to investing in Bitcoin and Ethereum, the availability of option implied volatility indices for these cryptocurrencies allows investors to trade on them and manage their cryptocurrency investment risk more effectively.

The insights from this study can also be valuable for policymakers and regulators in understanding the behavior of the cryptocurrency market. Given that cryptocurrencies represent a relatively untapped territory for regulators, traditional policy approaches used for other financial markets may not be entirely suitable. The various behavioral aspects discussed in this paper could offer insightful information for policymakers and regulators to navigate this dynamic landscape effectively.

In the future, it will be interesting to see how the cryptocurrency return-volatility relationship varies at different frequency intervals. For that, a similar study can be done using the high-frequency data (e.g., 1, 5, 10, 15, and 60- min ranges of data when available).

Data availability

Data will be made available on request.

Appendix A. Appendix

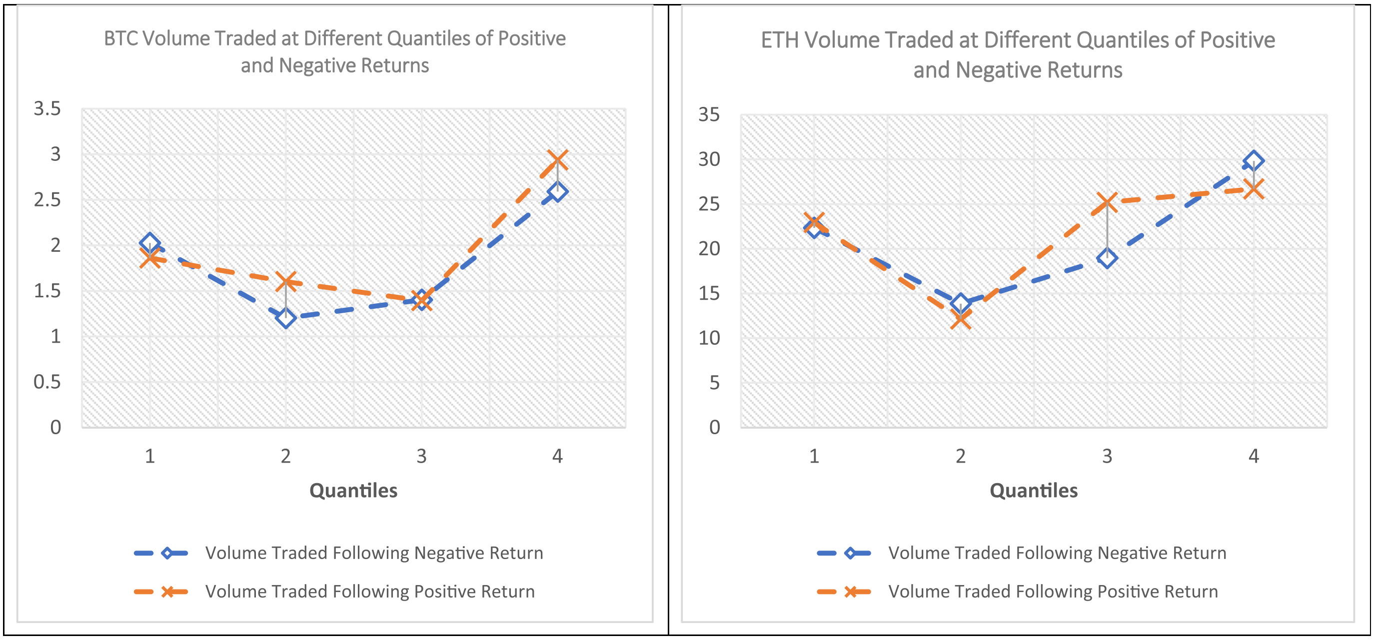

Fig. 9. Traded Volume of Bitcoin and Ethereum at Different Quantiles of Positive and Negative Returns

The left (right) panel of Figure-9 shows the volume of traded Bitcoin (Ethereum) at different quantiles of positive and negative returns. The volume data is based on the data provided by the Gemini Exchange.[12] The X-axis of the Figure-9 shows the different quantiles of the positive and negative returns; where, quantile 1 represents the lowest positive and negative return regimes, and quantile 4 presents the highest positive and negative returns regimes. Y-axis shows the volume traded. The volume is given in the transacted currency (i.e. for BTC/USD, this is in BTC amount).

1. The figure shows that the trading volume of Bitcoin and Ethereum increases as negative and positive return increase. It seems that following (both) positive and negative returns' shocks, the trading volume of Bitcoin and Ethereum increases.
2. Bitcoin traders trade more following the high positive return (following the good news). Whereas, Ethereum traders trade more following the bad news (when negative return increases). See the quantile- 4 of the Fig. 9.

It seems that the noise trading activities following a positive price movement are less (or absent) for Ethere.

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