Asymmetric interdependencies between large capital cryptocurrency and Gold returns during the COVID-19 pandemic crisis

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Abstract

This article explores asymmetric interdependencies between the twelve largest cryptocurrency and Gold returns, over the period January 2015 – June 2020 within a NARDL (nonlinear autoregressive distributed lag) framework. We focus our analysis on the epicentre of the first wave of the COVID-19 pandemic from March 2020 to June 2020. During this crisis, cryptocurrencies are more correlated and more of them have returns that are cointegrated with Gold returns. Moreover, cryptocurrencies develop a long-term as well as a short-term asymmetric response to Gold returns during the COVID-19 period where most cryptocurrency returns respond more to negative changes and exhibit more persistence with Gold returns. Overall, our most important result confirms that the connectedness between Gold price returns and cryptocurrency returns increase in economic turmoil, such as during the COVID-19 crisis.

Keywords: Cryptocurrencies; Gold; NARDL; Connectedness; COVID-19 crisis

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1. Introduction

In recent years, the growing importance of the cryptocurrency market has led to an exponential increase in the number of papers published in leading academic journals. In addition, the global impact of the COVID-19 crisis is multiplying the number of papers that include a specific analysis focused on this pandemic period. The aim of this paper is to study interdependencies between the largest cryptocurrency and Gold price returns with a focus on the epicentre of the first wave of the COVID-19 pandemic period, from March to June 2020.

The potential interdependence between the most popular cryptocurrencies and Gold has important implications for market participants because connectedness can affect the decision-making of investors (González *et al.*, 2020a, and Jareño *et al.*, 2020). If a given cryptocurrency is highly correlated with another financial asset such as Gold, then investors can construct a hedge portfolio consisting of a short position in the cryptocurrency and a long position in Gold to hedge overall risk. Alternatively, if the correlation is low, adding a long position in a cryptocurrency to an established portfolio will lead to further diversification potentially leading to an improvement in the risk to reward ratio. If the correlation is very low and stable, especially during times of market turbulence, then the cryptocurrency can form a safe haven by providing an asset for investors to park their cash until the market turbulence passes. Thus, a deep analysis of the connectedness between cryptocurrency and Gold markets can have a key role for implementing suitable investment strategies that allow investors to manage their portfolios more effectively.

González et al. (2020b) find that the contract structure of each cryptocurrency is different so there is no reason to suppose that all cryptocurrencies should behave in the same way, especially during a period of financial stress. Therefore, we conduct a currency-by-currency analysis by running separate regressions for each cryptocurrency against Gold to detect potential divergences among them to discover whether cryptocurrencies behave as a similar asset class like bonds or like stocks or are they a divergent set of assets like commodities.

In addition, an extensive study of interdependence between cryptocurrency and Gold returns during different economic conditions is crucial. Previous studies note that cryptocurrency connectedness with other assets could change over time, so this issue is relevant in a market as volatile as the cryptocurrency market, especially in periods of economic crisis such as the period affected by the COVID-19 pandemic. Consequently, investment strategies using cryptocurrencies as hedging, diversification or even as a safe haven asset could be influenced if the connectiveness of crypto coins change during a crisis period. To this end, this study analyses the behaviour of the main cryptocurrencies (Bitcoin and other large cap alternative coins –altcoins) during the COVID-19 crisis period.

Accordingly, this paper contributes to the previous literature in the following ways. First, our main contribution is to analyse in depth the dynamic rolling connectedness between twelve of the most popular cryptocurrencies and with another financial asset – Gold from January 2015 until June 2020. We discover that not all cryptocurrencies behave in the same way, for example Tether is much less connected to Gold that the other cryptocurrencies suggesting that Tether will perform best in a diversification role rather than as a hedging asset.

Second, this research focuses on the COVID-19 pandemic crisis to determine if the connectiveness of cryptocurrencies change in periods of economic distress. We accomplish this by examining two overlapping subperiods. The first is from January 2020 until June 2020 thereby incorporating the run up to and the heart of the first wave of the COVID-19 crisis period. The second subperiod examines the epicentre of the crisis from March 2020 until June 2020. Consistent with other research into more traditional financial assets (see Junior and Franca, 2012), during the COVID-19 crisis, cryptocurrencies are more correlated and more of them have returns that are cointegrated with Gold returns.

Third, we conduct our analysis using the NARDL regression technique which allows us to examine in a very general way the "connectiveness" of the most popular cryptocurrencies with Gold by examining not only the correlation, but also the cointegration, the long and short run asymmetries and the persistence in the relationship between a given cryptocurrency and Gold. We find that cryptocurrencies develop a long-term as well as a short-term asymmetric response to Gold returns during the COVID-19 period where most cryptocurrency returns respond more to negative than positive changes and exhibit more persistence with Gold returns. Overall, our most important result confirms that the connectedness between Gold and cryptocurrency returns increase during periods of economic turmoil, such as the COVID-19 crisis, suggesting that the hedging role of most cryptocurrencies improve during times of financial crisis just when a hedging asset is most needed.

This paper is related to Jareño et al. (2020) that also examines the connectiveness of Bitcoin with Gold using the NARDL approach. However, this paper extends the investigation from one to twelve major altcoins (unlike most previous studies that analyse exclusively Bitcoin or only 2-3 relevant cryptocurrencies, see Bouri et al., 2018; and Demir et al., 2020 as examples), studying the connectiveness of this expanded list of currencies to another financial asset Gold, and by focusing the analysis on the period of turbulence caused by the SARS-CoV-2 pandemic. We examine the connectiveness of this expanded list of cryptocurrencies with Gold because important variations in connectiveness would suggest that altcoins are alternative assets distinct from Bitcoin. It is notable that this paper discovers that Tether is much less connected to Gold than other cryptocurrencies.

The rest of the study is organized as follows. Section 2 shows a literature review of this fresh topic. Section 3 describes the data and methodology used in this research. Section 4 discusses the most relevant results and, finally, Section 5 collects some concluding remarks and mentions some directions for future research.

2. Literature review

Two branches of the recent literature have motivated this research. The first branch examines the connectedness between Bitcoin returns and returns of altcoins using different methodologies A second branch of the literature examine potential interdependencies between cryptocurrency returns and the returns of other asset classes. This paper seeks to connect these two branches of the literature by examining connectedness between the twelve largest cap cryptocurrencies and Gold price returns by applying the Nonlinear Autoregressive Distributed Lag (NARDL) approach and focussing this analysis on the recent COVID-19 crisis period.

In the first branch, many recent studies focus on analysing connectedness between Bitcoin and altcoins. Some of them use the NARDL approach to perform this analysis, such as González et al. (2020a) who find significant and positive connectedness among cryptocurrencies and significant long-run relationships among most of them. In addition, they find evidence of short-run asymmetry and high persistence in the impact of both positive and negative changes in Bitcoin returns on most altcoins returns. Thus, the NARDL approach explains about 50% of the other cryptocurrency returns with changes in Bitcoin returns. Demir et al. (2020) also use the Nonlinear Autoregressive Distributed Lag (NARDL) model to study the asymmetric effect of Bitcoin on three altcoins. They find an asymmetric impact of Bitcoin on altcoins in the short-run where a decrease in Bitcoin price has a greater effect than an increase on the prices of altcoins.

Within this first branch, we also find works that use different methodologies to study the connectedness between cryptocurrencies. Omane-Adjepong and Alagidede (2019) examine market connectedness of seven leading cryptocurrencies using Wavelet-based methods and parametric and nonparametric tests. Their results confirm the need to incorporate cryptocurrency market dynamics when adopting trading strategies. Shi et al. (2020) apply the multivariate factor stochastic volatility model (MFSVM) with the Bayesian estimation procedure for studying potential correlations among six cryptocurrencies (Bitcoin, Dash, Ethereum, Litecoin, Ripple, and Stellar). They find that Bitcoin is mainly associated with Litecoin, but Ethereum is related to other cryptocurrencies, so these results are very useful for managing trading strategies. Moreover, this paper points out the need for examining the connectedness between cryptocurrencies and traditional assets.

Kumar and Anandarao (2019) provide results along the same lines by studying the dynamics of volatility spillover across four major cryptocurrency returns (Bitcoin, Ethereum, Ripple and Litecoin), combining an IGARCH (1,1)-DCC (1,1) multivariate GARCH model with conditional correlation and wavelet coherence measures. They find evidence of turbulence and potential herding behaviour in the cryptocurrency markets, so, according to Kumar and Anandarao (2019), it would not be prudent to consider cryptocurrencies on par with traditional investments. Thus, we observe different conclusions regarding the inclusion of altcoins in traditional investments that make it necessary to go deeper into this research topic.

A similar study is presented by Ferreira et al. (2020), as they use estimated detrended cross-correlation (DCCA) and detrending moving-average cross-correlation (DMCA) coefficients to study potential interdependencies between six cryptocurrencies (Bitcoin, DASH, Stellar, Litecoin, Monero, and Ripple). They find that these (inefficient) cryptocurrencies behave differently from the random walk (efficient) dynamics of the stock markets. Thus, there is evidence of connectedness between several virtual currencies.

Some empirical papers, such as Chaim and Laurini (2019), apply a multivariate stochastic volatility model with discontinuous jumps to mean returns and volatility and state that the returns and volatility dynamics of relevant cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Monero, NEM, and Verge) is featured by large fluctuations in price, and long memory in volatility. More evidence of return and volatility spillovers can be found in Tu and Xue (2019). They examine potential interdependencies between Bitcoin and its substitute, Litecoin, by using the Granger causality test and a BEKK-MGARCH model. They find return and volatility spillovers only from Bitcoin to Litecoin.

Finally, within the connectiveness financial literature, recent papers focus their analysis on the pandemic crisis period caused by the COVID-19, such as Shahzad et al. (2021) who study the daily return spillover among 18 cryptocurrencies under low and high volatility regimes by applying a Markov regime-switching (MS) vector autoregressive model with exogenous variables (VARX). The empirical results provide evidence of strong spillovers across the cryptocurrency markets in low and high volatility regimes, especially during the COVID-19 outbreak. Yousaf and Ali (2020) analyse the return and volatility spillover between three major cryptocurrencies (Bitcoin, Ethereum, and Litecoin) during the pre-COVID-19 period and the COVID-19 period by implementing the VAR-AGARCH model to intra-day data. They find that the constant conditional correlations between all pairs of cryptocurrencies are observed to be higher during the COVID-19 period. Moreover, the hedging effectiveness is higher during the COVID-19 period. They highlight that their findings provide useful information regarding portfolio diversification, hedging, forecasting, and risk management. Corbet et al. (2020) study potential interdependencies between the largest cryptocurrencies by applying the standard GARCH model. They find evidence that relevant cryptocurrencies not only provide diversification benefits for investors but also acted as a safe-haven during this pandemic COVID-19 crisis period, a period characterised by marked financial market stress. In contrast, Conlon and McGee (2020), who analyse Bitcoin properties by employing the two-moment value at risk (VaR) method, suggest that Bitcoin does not act as a safe alternative asset as Bitcoin decreases in price in lockstep with the S&P 500 as the COVID-19 crisis develops. So, their empirical findings cast doubt on the ability of Bitcoin to provide safe alternative against turbulence in traditional markets. These contradictory results invite further analysis to try to provide evidence in one way or another.

In the second branch, there are many papers studying interdependences between cryptocurrencies and different asset classes. This research could be crucial for market participants using cryptocurrencies to implement hedging, diversification and safe haven strategies during crisis periods such as the COVID-19. In this line, Jareño et al. (2020) explore potential asymmetric interdependencies between Bitcoin and Gold price returns in the short- and long-run by applying the NARDL approach and obtain a positive and statistically significant interconnectedness that implies that Bitcoin could be used to form hedges during economic turmoil. Selmi et al. (2018) do a comparison between the role of Bitcoin and Gold as a hedge, a safe haven and/or a diversifier in different market conditions, finding evidence in favour of Bitcoin as a safe haven during political and economic crisis periods. Klein et al. (2018) agree and even call Bitcoin the New Gold. In the same vein, Guesmi et al. (2019) conclude that portfolios consisting of oil, Gold and stocks may decrease their risk by incorporating virtual coins, more specifically, Bitcoin. Canh et al. (2019) analyse the diversification capability of major cryptocurrencies against shocks in oil and Gold price and find that cryptocurrencies have insignificant correlations with economic risk factors, which implies a useful diversification capability. Symitsi and Chalvatzis (2019) study the performance of benchmark portfolios of currencies, Gold, oil and stocks as well as a multi-asset portfolio of currencies, Gold, oil, stocks, real estate and bonds with alternative portfolios that invest additionally in Bitcoin. This analysis was conducted for four trading strategies, both in bullish and bearish cryptocurrency market conditions. They find statistically significant diversification benefits from the inclusion of Bitcoin which are more pronounced for commodities such as oil. Charfeddine et al. (2020) evaluate the potential economic and financial benefits of cryptocurrencies for investors and conclude that these cryptocurrencies can be suitable for diversification, although they are poor hedging instruments in most cases. These authors also study the relationship between cryptocurrencies and conventional assets and find that this relationship is sensitive to economic and financial shocks.

In this second branch, there is more research that analyse the connectedness between cryptocurrencies and Gold, as well as other assets. Only Bouri et al. (2018) apply the NARDL approach, among other advanced autoregressive distributed lag (ARDL) models, to study the nonlinear, asymmetric and quantile effects of aggregate commodity indexes and Gold prices on the price of Bitcoin. Moreover, they extend the NARDL model to a quantile framework to test for distributional asymmetry and to account for short- and long-run asymmetries. They indicate that Bitcoin price movements can be predicted based on price information from an aggregate commodity index and Gold prices and suggest the need to apply non-standard cointegration models to uncover the complexity and hidden relations between Bitcoin and other asset classes. However, neither this nor any of the following papers that also analyse the connection between cryptocurrencies and Gold are focused on the COVID-19 crisis period.[1]

Thus, Ji et al. (2019) explores potential interconnectedness between several commodities (energy, metals and agricultural) and cryptocurrencies, finding that this connectedness is time-dependent, and cryptocurrencies are integrated within commodity markets. Therefore, investors should consider interdependencies between commodities and cryptocurrencies when making investment decisions. Adebola et al. (2019). explore potential (short and long run) linkages between major cryptocurrencies (Bitcoin, Bitshare, Bytecoin, Dash, Ether, Litecoin, Monero, Nem, Ripple, Siacoin, Stellar and Tether) and Gold prices using fractional integration and cointegration techniques. They find cointegration in only a few cases with only a small degree of cointegration in the long run.

Finally, Rehman and Vo (2020) investigate the relationship between cryptocurrency and precious metal (Gold, silver, copper, platinum, palladium and nickel) returns. They use a quantile cross spectral framework to analyse changing correlation patterns across different quantile distributions under short-, medium- and long run investment horizons. They find that copper provides maximum diversification opportunities for all cryptocurrencies in the short run. Meanwhile, for medium- and long-run investment periods, precious metals under extreme positive return distributions are not integrated with extreme negative cryptocurrency returns, thereby implying diversification opportunities for investors.

Table A1 summarizes the main characteristics and key findings of the literature reviewed in this section. Overall, we note that there is a need to examine the connectiveness between cryptocurrencies and other financial assets such as Gold during the COVID-19

[1] Although Bouri et al. (2021) do indeed study the connectedness between various assets (Gold, crude oil, world equities, currencies, and bonds) around the COVID-19 outbreak, but not with cryptocurrencies.

pandemic because they present opportunities for investors to yield optimal portfolio returns by including them, especially as we move into a severe financial crisis. This is a gap that we address in this paper. We expect that the connectiveness between cryptocurrencies and Gold will increase during the COVID-19 crisis period. In addition, according to Demir et al. (2020) and González et al. (2020a), among others, increases and decreases in the Bitcoin price may have different effects on altcoins, so in the present study it would be interesting to look for the presence of an asymmetric effect of Gold price returns on Bitcoin and other major altcoin returns in the short- and long-run. We intend to accomplish this by applying the NARDL approach (Jareño et al., 2020). Moreover, these previous studies suggest that potential asymmetric interdependencies between cryptocurrency and Gold returns may be different depending on the state of the economy, such as the current economic turmoil caused by the coronavirus pandemic. Interdependencies between cryptocurrency and Gold returns in terms of asymmetry and non-linearity seem to have been under explored in previous studies (Bouri et al., 2018).

3. Data and Methodology

3.1. Data

The data used in this paper is from the coinmarketcap website and consist of daily log returns of the top twelve cryptocurrencies ranked by market capitalization for a sample period from January 26, 2015 to June 30, 2020. Table 1 reports these twelve cryptocurrencies ordered by market capitalization on June 30, 2020, namely Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Ripple (XRP), Bitcoin_cash (BCH), Bitcoin_sv (BSV), Litecoin (LTC), Binance_coin (BNB), Crypto.com Coin (CRO), EOS, Cardano (ADA) and Tezos (XTZ). These top twelve cryptocurrencies represent, on average, almost 89% of the cryptocurrency market capitalization and Bitcoin alone has an approximately 65% share in this market, on June 30, 2020.

[Please, insert Table 1 about here]

The whole sample period, from January 26, 2015 to June 30, 2020, yields about 2,000 daily data observations. The beginning of the period is determined by the availability of data and the end of the period by the most recent possible data for the current COVID-19 crisis.

Figure 1 plots the time evolution of the cryptocurrency daily prices to the end of June 2020 and so incorporates the COVID-19 pandemic crisis subperiod. In detail, the pandemic sub-period includes not only the most virulent first wave of the COVID-19 disease (mainly from March 2020, highlighted in orange), but also some previous months (from January 2020 to March 2020, highlighted in yellow), when we knew about the existence of the coronavirus, but it had not yet become a pandemic. Therefore, this subperiod includes a period of pre-crisis and the epicentre of true COVID-19 pandemic crisis.

[Please, insert Figure 1 about here]

The cryptocurrency market has been shaken by the COVID-19 crisis. The first major collapse occurred on March 8, with massive sales in the cryptocurrency market culminating in the fall of the stock markets all over the world on March 9 (Black Monday). Due to this massive sale, the cryptocurrency market lost $21 billion in market capitalization in twenty-four hours from Saturday, March 7, 2020 to Sunday, March 8, 2020, going from a total capitalization of the cryptocurrency market from $251.5 billion to $230.8 billion. Moreover, just six days later, on March 13, 2020, the cryptocurrency market had lost $125.4 billion, almost half of its total capitalization, falling to a total capitalization of only $126.1 billion, while trading volume that day amounted to more than $196 billion. As a result, the market capitalization of the ten major cryptocurrencies fell sharply during that week, being heavily affected by the COVID-19 crisis (March 7-13). In particular, the capitalization of the cryptocurrencies fell between 37.4% (XRP) and 51.7% (Tezos) and their prices between 42.4% (XRP) and 56.3% (Bitcoin SV). Exceptionally, Tether experienced an increase in its market capitalization and its price, making it climb up the ranking of the ten main cryptocurrencies.

However, the cryptocurrency market has since progressively recovered to a total capitalization higher than before the massive sale on March 8, surpassing $281 billion on June 11, 2020 and remaining above $260 billion throughout June 2020. At the same time, the capitalization and the price of these cryptocurrencies also managed to rise and most of them have reached values in June 2020 higher than those presented before the massive sale on March 8, 2020. Furthermore, it is worth noting that, despite the large drop in the capitalization of the cryptocurrency market, Bitcoin has always maintained its dominant position over the other virtual currencies, with a share of over 64% in the cryptocurrency market.

Table 2 collects the descriptive statistics and unit root tests of the twelve cryptocurrency returns for daily data for the entire sample period. All cryptocurrencies show similar positive mean log-returns, except for Cardano, EOS, Bitcoin_cash and Tezos that show low but negative mean values. The highest positive mean return is for CRO. Meanwhile, XRP and Bitcoin_sv show the highest standard deviations (more than 10%), and Gold shows the lowest standard deviation. About half of the cryptocurrency returns show positive skewness, and all the cryptocurrency and Gold price returns exhibit excess kurtosis. The standard Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test confirm that all variables are stationary.

[Please, insert Figure 2 about here]

[Please, insert Table 2 about here]

3.2. Methodology

To study the asymmetric interdependencies between the twelve most popular cryptocurrency and Gold price returns, the nonlinear autoregressive distributed lag (NARDL) model developed by Shin et al. (2014) is applied to simultaneously capture both long- and short-run asymmetries between these variables.

According to Shin et al. (2014) and Jareño et al. (2019), this methodology enables us to measure the separate responses to positive and negative shocks of the regressors from the asymmetric dynamic multipliers. More specifically, the asymmetric long-run regression between the top twelve cryptocurrencies and Gold price returns is an approach to modelling asymmetric cointegration based on partial sum decompositions:

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

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

where R_{jt} and GR_t are scalar I(1) variables. In detail, R_{jt} is the cryptocurrency return corresponding to period t, GR_t is the Gold price returns for period t which is decomposed as $GR_t = GR_0 + GR_t^+ + GR_t^-$, where GR_t^+ and GR_t^- are partial sums of positive and negative changes in Gold price returns, ε_{jt} and v_t are random disturbances and $\alpha = (\alpha_0, \alpha^+, \alpha^-)$ is a vector of long-run parameters to be estimated. More specifically, the coefficients α^+ and α^- capture the long-run relation between the twelve most relevant cryptocurrency returns and increases (α^+) or decreases (α^-), respectively, in Gold price returns.

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

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

Shin et al. (2014) extended the well-known linear autoregressive distributed lag (ARDL) bounds testing approach popularised by Pesaran and Shin (1999) and Pesaran et al. (2001) and proposed the dynamic, asymmetric and non-linear NARDL(p,q) model:

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

[5]

where GR_t is a kx1 vector of multiple regressors defined such that $GR_t = GR_0 + GR_t^+ + GR_t^-$, ϕ_i is the autoregressive parameter, p is the number of lagged dependent variables and q is the number of lags for regressors, γ_i^+ and γ_i^- are the asymmetric distributed-lag parameters, and, finally, ε_{jt} is an *iid* process with zero mean and constant variance σ_ε^2.

Additionally, $\alpha^+ = -\beta_2/\beta_1$, $\alpha^- = -\beta_3/\beta_1$, are the coefficients of long-run impacts of Gold price return increases and decreases respectively on each of the twelve most popular cryptocurrency returns. On the other hand, $\sum_{i=0}^{q} \gamma_i^+$ and $\sum_{i=0}^{q} \gamma_i^-$ measure the short-run influences of increases and decreases, respectively, of Gold price returns on each of the top twelve cryptocurrency returns. Therefore, the NARLD model captures both the asymmetric long-run and short-run impact of Gold price return changes on the top twelve cryptocurrency returns to distinguish the response of economic agents to positive and negative shocks.

Finally, we estimate the proposed NARDL model using stepwise regression under ECM (Error Correction Model) because it improves the performance of the NARDL model in small samples and increase the power of the cointegration tests. Moreover, Shin et al. (2014) affirm that the dynamic adjustment of the NARDL model in the error correction form maps the gradual movement of the process from initial equilibrium through the shock and towards the new equilibrium.

4. Results

This section reports the NARDL model estimates between daily Gold price returns and the top 12 cryptocurrency returns for the whole sample period from January 2015 to June 2020 in the first sub-section, for the epicentre of the first wave of the COVID-19 period from March to June 2020 in the second sub-section and, finally, for the expanded COVID-19 period from January to June 2020 in the third sub-section.[2] We test for the presence of asymmetry and cointegration in the relations between Gold price returns and the top twelve cryptocurrency returns. Specifically, we study the connectedness between these variables by the Pearson's correlation coefficients defined by the null hypothesis of no correlation (H_0: *PCorr=0*); the presence of cointegration by the Wald F test for the joint null hypothesis that coefficients on the level variables are jointly equal to zero (H_0: $\beta_1 = \beta_2 = \beta_3 = 0$); the cointegration equation (long-run elasticities) between variables; the long-run symmetry by means of the Wald test, with symmetry implying H_0: $-\beta_2/\beta_1 = -\beta_3/\beta_1$.; the short-run symmetry in the short-run model by the Wald test for the null of short-run symmetry defined by $\gamma_i^+ = \gamma_i^-$ and the effect of the cumulative sum of positive and negative changes (respectively) in Gold price returns for 1 to 4 lags on the top twelve cryptocurrency returns.

4.1. Results of the NARDL models: whole sample period (January 26, 2015-June 30, 2020)

Table 3 shows the regression results of the NARDL models and the asymmetry and cointegration tests between Gold price returns and the top twelve cryptocurrency returns for the whole sample period from January 26, 2015 to June 30, 2020. Specifically, this table contains the Pearson's correlation coefficients in column 2, the Wald test for the presence of long-run relation or cointegration between Gold price returns and the top twelve cryptocurrency returns in column 3, the cointegration equation between these variables in column 4, the Wald test for long-run and short-run symmetry in columns 5 and 6, respectively, the effect of the cumulative sum of positive and negative changes in

[2] It is noteworthy that the maximum lag order considered in these NARDL estimations is 4.

Gold price returns for one to four lags on the top twelve cryptocurrencies in columns 7 and 8, respectively and the Adjusted R^2 of each cryptocurrency in the last column.

[Please, insert Table 3 about here]

The Pearson correlation coefficients reported in column 2 show that the null hypothesis of no correlation (H_0: $PCorr=0$) is rejected at the 1% statistical significance level by all the top twelve cryptocurrencies except for Tether. A positive correlation is observed between Gold price returns and the remaining eleven cryptocurrency returns with Pearson correlation coefficients between 14.48% (Bitcoin_SV) and 29.67% (Bitcoin). The Pearson correlation coefficients show values higher than those obtained in previous similar studies, such as Jareño *et al.* (2020), which focuses only on the study of Bitcoin. In contrast, this paper analyses the connection between Gold price returns and the returns of the twelve most important cryptocurrencies currently operating in that market.

The Wald F test for the presence of cointegration, contained in column 3, shows that three cryptocurrencies (XRP, Tether and Cardano) reject the null hypothesis of no cointegration (when on the level variables are jointly equal to zero, H_0: $\beta_1 = \beta_2 = \beta_3 = 0$). Therefore, this F-test shows cointegration between changes in Gold price returns and XRP, Tether and Cardano returns for the whole sample period. In addition, the cointegration coefficients of changes in Gold price returns are positive for these three cryptocurrencies and statistically significant at 1% level for XRP and Tether, with the highest values, and at 5% level for Cardano.

The cointegration equation between Gold price returns (GR) and the top twelve cryptocurrency returns (R_{jt-i}), $R_{jt-i} = e^{+} \cdot GR^{+}_{t-i} + e^{-} \cdot GR^{-}_{t-i}$, exhibited in column 4, shows the long-run elasticities for the cumulative sum of positive (GR^{+}_{t-i}) and negative (GR^{-}_{t-i}) changes in Gold price returns, respectively. The results of this equation provide evidence that all cryptocurrency returns respond in the same direction to positive and negative changes in Gold price returns. In addition, the coefficients are quite similar for all cryptocurrencies except for EOS, Cardano and CRO that show asymmetry by responding more to negative than to positive changes in Gold price returns. Additionally, the long-run elasticities for the cumulative sum of positive and negative changes in Gold price returns are statistically significant only for Bitcoin_SV at the 10% significance level. The coefficients are large and positive (3.29 and 4.29) meaning Bitcoin SV responds more and moves in the same direction to positive and negative changes as Gold price returns.

The Wald test for studying long-run symmetry provided in column 5 shows that the null hypothesis of long-run symmetry (H_0: $-\beta 2/\beta 1 = -\beta 3/\beta 1$) is not rejected by any cryptocurrency and therefore, there is no evidence of asymmetry in the long-run impact of Gold price on any cryptocurrency for the whole sample period.

The Wald test for short-run symmetry reported in column 6 shows that the null hypothesis of short-run symmetry (H_0: $\gamma_i^+ = \gamma_i^-$) is rejected by all the cryptocurrencies, except XRP and Tether, as they show positive and statistically significant coefficients at the 1% level. This is strong evidence of asymmetric short-run responses of ten out of twelve cryptocurrency returns to changes in Gold price returns for the whole sample period. Thus, nonlinear asymmetries are important in the short-run relationship between Gold price returns and these ten cryptocurrency returns for the full period.

The effect of the cumulative sum of positive and negative changes in Gold price returns for 1 to 4 lags for the top twelve cryptocurrency returns is reported in columns 7 and 8, respectively. They report high persistence in the effect of both positive and negative changes in Gold price returns, for 1 to 4 lags, for most cryptocurrency returns. In particular, there is a statistically significant cumulative sum of positive changes in Gold price returns for five out of twelve cryptocurrency returns with a positive sign on Bitcoin and Bitcoin_cash returns for 2 lags and, contrarily, with a negative sign on Ethereum returns for 1-lag and Bitcoin_cash, EOS and Binance_coin returns for 4-lags. On the other hand, there is a negative and statistically significant cumulative sum of negative changes in Gold price returns for nine out of twelve cryptocurrency returns for 1-lag and for three, namely Bitcoin_sv, Binance and Crypto.com_coin returns for 1- and 3-lags.

Finally, the explanatory power of the NARDL model as reported in the last column of Table 3 varies from a minimum of 1.53% for Bitcoin to a maximum of 12% for Tether returns. These results are similar but slightly higher than those found by other researchers such as Jareño *et al.* (2020) at least in part because we study 11 altcoins in addition to Bitcoin.

4.2. Results of the NARDL models: the epicentre of the first wave of the COVID-19 pandemic crisis sub-period (March 1-June 30, 2020)

Table 4 shows the regression results of the NARDL models and the asymmetry and cointegration tests between Gold price returns and the top twelve cryptocurrency returns for the heart of the COVID-19 pandemic crisis sub-period from March 1 to June 20, 2020. This table has the same organization as table 3.

[Please, insert Table 4 about here]

The second column of Table 4 shows the Pearson correlation coefficients between Gold price returns and the top twelve cryptocurrency returns and states that the null hypothesis of no correlation is rejected by all cryptocurrencies except, once again, for Tether. Thus, except for Tether, there is a positive correlation, ranging from 32% to 45.95%, between Gold price returns and cryptocurrency returns at the 1% significance level. This result suggests that the largest cryptocurrencies would exhibit a higher level of correlation with Gold prices during the epicentre of the COVID-19 crisis than the whole sample from January 2015- June 2020.

The third column of Table 4 reports the Wald's F test for the presence of cointegration and this test shows that the null hypothesis of no cointegration is rejected by all cryptocurrencies except for Tezos. Additionally, the long-run coefficients of changes in Gold price returns are positive and statistically significant at 1% level for ten out of the eleven significant cryptocurrencies for this pandemic crisis sub-period.

The fourth column of Table 4 reports the cointegration equation between Gold price returns and the top twelve cryptocurrency returns and shows that all cryptocurrency returns respond in the same direction to positive and negative changes in Gold price returns. Additionally, most cryptocurrency returns respond more to negative changes in Gold price returns because all of them have a larger negative response coefficient. For instance, a 10% increase in Gold price returns is related to a 1.5% increase in Cardano returns but a 10% decrease in Gold price returns leads to a 15.7% decrease in Cardano returns. Moreover, the long-run elasticities for the cumulative sum of positive and negative changes in Gold price returns are statistically significant for most cryptocurrencies. Most coefficients are positive, except for Tether which has negative coefficients. Bitcoin_sv shows the largest coefficients (58% and 72%) meaning that Bitcoin_sv responds the most and moves in the same direction to positive and negative changes in Gold price returns.

The fifth column of Table 4 exhibits the Wald test for long-run symmetry and shows that the null hypothesis of long-run symmetry is rejected by ten out of twelve cryptocurrencies. The significant coefficients are positive and are significant at either the 1% or 5% levels. Therefore, there is strong evidence of the asymmetric long-run impact of Gold price returns on these ten cryptocurrency returns during the epicentre of the COVID-19 crisis.

The sixth column of Table 4 reports the Wald test for short-run symmetry and shows that the null hypothesis of short-run symmetry is rejected by all the cryptocurrencies. In particular, all cryptocurrencies show positive and statistically significant coefficients at the 1% significance level, except Tether which shows a negative coefficient also at 1% significance level. Thus, there is strong evidence of asymmetric short-run responses of all cryptocurrency returns to changes in Gold price returns during the heart of the COVID-19 crisis. Therefore, nonlinear asymmetries are operative not only for the long-run but also for the short-run relationship between Gold price and almost all the top twelve cryptocurrencies for the height of the COVID-19 pandemic crisis.

The seventh and eighth columns of Table 4 report the effect of the cumulative sum of positive and negative changes in Gold price returns for 1 to 4 lags for the top twelve cryptocurrency returns. These coefficients exhibit a high persistence on the impact of both positive and negative changes in Gold price returns, for 1 to 4 lags, for virtually all the top twelve cryptocurrency returns. These results also illustrate that there is a statistically significant and slightly larger short-run impact of increases than decreases of Gold price returns for most cryptocurrencies returns. Additionally, we observe a negative and statistically significant response of the cumulative sum of positive changes in Gold price returns on Bitcoin returns for 2-lags and on Tether returns for 3-lags. We also observe a positive and statistically significant effect of the cumulative sum of negative changes in Gold price returns for Tether and a negative and statistically significant effect of the cumulative sum of negative changes in Gold price returns for eight of the remaining cryptocurrencies.

Overall, the explanatory power of the NARDL model as measured and reported in column 9 of Table 4 varies from a minimum of 38.72% for CRO returns to a maximum of 49.71% for Tezos returns. It is notable that the values of the adjusted R^2 in the epicentre of the COVID-19 crisis is four times their values for the whole sample period.

4.3. Results of the NARDL models: expanded COVID-19 pandemic crisis subperiod (January 1-June 30, 2020)

Table 5 shows the regression results of the NARDL models and the asymmetry and cointegration tests between Gold price returns and the top twelve cryptocurrency returns for the expanded COVID-19 pandemic crisis sub-period from January 1 to June 30, 2020. This COVID-19 sub-period includes not only the most virulent moment of the first wave of the COVID-19 disease, but also some previous months, when we knew about the existence of the coronavirus, but only gradually realised its significance. Therefore, this subperiod includes a period of pre-crisis and the period of the true pandemic crisis.

[Please, insert Table 5 about here]

The Pearson correlation test reported in the second column of Table 5 finds a positive and statistically significant relation between Gold price returns and all the cryptocurrency returns. Most of the correlations are statistically significant at the 1% level and only Bitcoin_sv and Tether are significant at 5% and 10% level, respectively. Moreover, the Pearson's correlation coefficients in this expanded COVID-19 sub-period, ranging between 20.2% for Bitcoin_sv and 42.3% for Binance_coin, are not as high as in the heart of COVID-19 crisis but they do exceed the values of the coefficients for the whole sample period.

The results of the Wald's F test for cointegration, reported in the third column of Table 5, show that the null hypothesis of no cointegration is rejected by all the cryptocurrencies. The F-statistics show long-run connectedness, or cointegration, between variations in Gold price returns and all the top twelve cryptocurrency returns in this expanded COVID-19 sub-period. Additionally, the long-run coefficients of changes in Gold price returns are positive for all the cryptocurrencies and are statistically significant at least at the 10% level.

The results of the cointegration equation listed in the fourth column of Table 5 show that all cryptocurrency returns respond in the same direction to positive and negative changes in Gold price returns. Additionally, the coefficients are quite similar for most cryptocurrencies. Furthermore, the long-run elasticities for the cumulative sum of positive and negative changes in Bitcoin returns are statistically significant for all twelve cryptocurrencies and their coefficients are positive for all except Tether. Finally, Bitcoin_sv exhibits the largest coefficients (5.03 and 5.81) and it responds more and in the same direction to positive and negative variations in Gold price returns.

The results of the Wald test for testing the long-run symmetry, reported in the fifth column of Table 5, show that the null hypothesis of long-run symmetry is rejected by five out of twelve cryptocurrencies, indicating that there is asymmetry on the long run impact of Gold price returns for Bitcoin, Bitcoin_cash, Tether, Litecoin and CRO returns in this expanded COVID-19 sub-period.

The results of the Wald test for testing the short-run symmetry, reported in the sixth column of Table 5, show that all the cryptocurrencies reject the null hypothesis of short-run symmetry. Moreover, all of them show positive and statistically significant coefficients at the 1% level except for Tether which has negative coefficients. Therefore, all cryptocurrency returns show asymmetric short-run responses to changes in Gold price returns in the expanded COVID-19 sub-period.

The effect of the cumulative sum of positive and negative changes in Gold price returns for 1-4 lags for the top twelve cryptocurrency returns, exhibited in the seventh and eight columns of Table 5, show that there is no impact of positive changes in Gold price returns on any cryptocurrency. Nevertheless, we observe a high persistence for negative variations in Gold price for eight of the cryptocurrencies returns in this expanded COVID-19 sub-period.

The explanatory power of the daily NARDL model varies from a minimum adjusted R^2 of 24.6% for EOS returns to a maximum of 38.5% for Ethereum returns. Additionally, the values of the adjusted R^2 in this expanded COVID-19 sub-period is somewhat lower than in the heart of the COVID-19 sub-period. The lower R^2 can be explained by the longer subperiod that includes a pre-crisis period, so the statistically significant effect could be softened.

Therefore, due to the higher explanatory power and stronger and more significant detailed results of the NARDL model during the epicentre of the COVID-19 crisis than during the expanded COVID-19 and the overall sample time periods, we find evidence that confirms our initial hypothesis that interdependencies between Gold price returns and cryptocurrency returns is strengthened in periods of economic turbulence, such as the COVID-19 pandemic crisis.

4.4. Additional Analysis

In this section we conduct two additional analysis by examining the quantile behaviour and a more detailed examination of the asymmetric response of cryptocurrency returns to Gold returns.

4.4.A A quantile dependence study

According to Sevillano and Jareño (2018), Jareño et al. (2020) and Jareño et al. (2021), among others, the Quantile Regression (QR) methodology, combined with the NARDL approach, allows for a richer study by considering estimates across (low, medium, and high) quantiles during bearish, normal and bullish markets. To test quantile cross dependence between cryptocurrency and Gold markets, Figure 3 plots the sensitivity of estimates to changes in Gold price returns for the dominant cryptocurrency returns explored in this study. In addition, this paper analyses asymmetric interdependencies between the twelve major cryptocurrency and Gold returns and allows us to separately consider not only positive and negative changes but also the impact of the cumulative sum of positive and negative changes of Gold price returns on the leading cryptocurrency returns.

In Figure 3, the horizontal axis shows the quantiles of the conditional distribution of cryptocurrency returns and the vertical axis the estimated sensitivities of the explanatory variables to Gold price returns. These graphs report the positive and negative changes (GOLD_P and GOLD_N) and the cumulative sum of positive and negative changes (DGOLD_P and DGOLD_N) of Gold prices and significant lags () of them as extracted from the NARDL model. The solid blue line illustrates the QR coefficient estimates and the solid red lines indicate the corresponding 90 per cent confidence intervals. These graphs confirm that responses to changes in Gold price returns are different at extreme quantiles with respect to the median. Therefore, additional information can be gleaned by combining the nonlinear autoregressive distributed-lag approach with a quantile regression to jointly explore short-run dynamics and long-run cointegrating relationships across a range of quantiles.

[Please, insert Figure 3 about here]

4.4.B Asymmetric dynamic multipliers

Figure 4 plots the Asymmetric Dynamic Multipliers that show the impact of positive and negative changes of Gold prices on cryptocurrency returns. The horizontal axis shows the period in days and the vertical axis the multiplier for positive (continuous black line) and negative (dashed black line) changes in Gold prices and the asymmetry (dashed red line) with 95% bootstrap confidence interval based on 1000 replications.

For most cryptocurrency returns the impact of positive and negative Gold price changes become stable after 4-5 days. However, substantial differences are observed for several cryptocurrencies. Some cryptocurrencies, such as Ethereum, Litecoin, Eos, Tezos and Cardano, exhibit a larger impact for negative rather than positive changes in Gold prices while XRP and Tether do not show an asymmetric response. This dissimilar behavior among the alternative currencies has important implications for portfolio management. Moreover, these interesting results may open a new line of work to be addressed in future research as noted in the concluding remarks.

[Please, insert Figure 4 about here]

5. Concluding Remarks and Directions for Future Research

The aim of this paper is to analyse long- and short-run interdependencies between Gold price returns and the returns of the top twelve cryptocurrencies because these relationships could be crucial for market participants when implementing investment strategies. We analyse the asymmetric interdependences by applying the non-linear autoregressive distributed lag NARDL model developed by Shin et al. (2014) over a sample period that runs from January 2015 to June 2020. Additionally, we consider the stage of the pandemic crisis because the previous literature suggests that interdependence patterns may change over time. To this end, this paper compares the results of the full period with the results of two subperiods for the COVID-19 crisis: the epicentre of the first wave of the COVID-19 crisis from March to June 2020 and the expanded COVID-19 crisis period from January to June 2020 that traces the evolution of the pandemic.

The main contribution of this paper is that, to the best of our knowledge, this is the first study that analyses the connectedness between Gold price and the top twelve cryptocurrencies by using the NARDL approach to assess both long- and short-run asymmetries not only in the whole sample period but also in the COVID-19 crisis sub-period.

The main conclusions are as follows. First, there is a positive and statistically significant correlation between Gold price returns and all the top twelve cryptocurrency returns, except for Tether, not only for the entire period but also for the two COVID-19 sub-periods. This correlation is particularly strong during the epicentre of the coronavirus crisis. Second, there is cointegration or long-run connectedness between changes in Gold price returns and all cryptocurrencies returns in the expanded COVID-19 sub-period and all cryptocurrencies except Tezos during the epicentre of the COVID-19 crisis and just three cryptocurrencies in the whole sample period. Therefore, cointegration is clearly increased during the COVID-19 period. Third, the long-run elasticities for the cumulative sum of positive and negative changes in Gold price returns are statistically significant for all cryptocurrencies in the expanded COVID-19 sub-period, for ten out of twelve cryptocurrencies in the epicentre of the COVID-19 crisis and for just one cryptocurrency, Bitcoin_sv, in the entire sample period. Most of the long run elasticities are positive, except in the case of Tether which always shows negative elasticities. Additionally, Bitcoin_sv shows the largest coefficients not only in the whole sample period but also in the two COVID-19 sub-periods. Fourth, while there is no evidence of asymmetry in the long-run impact of Gold price returns on cryptocurrency returns for the whole sample period, this asymmetry is operative for five out of twelve cryptocurrencies during the expanded COVID-19 sub-period and for ten out of twelve cryptocurrencies returns during the most severe COVID-19 sub-period suggesting stronger evidence of asymmetry in the long run during the epicentre of the COVID-19 crisis. In addition, there is strong evidence of short run asymmetries between Gold price returns and all the cryptocurrencies' returns for both COVID-19 sub-periods and ten out of twelve cryptocurrency returns in the full sample period. Fifth, there is evidence of high persistence in the effect of both positive and negative changes in Gold price returns, for 1 to 4 lags, for most of the cryptocurrency returns. Finally, the NARDL model explains an increasing amount of the response of cryptocurrency returns to Gold returns as we move into the epicentre of the COVID 19 crisis. In particular, the NARDL model explains more than 12%, 38% and 49% of the cryptocurrency returns with changes in Gold price returns for the whole sample period, the expanded COVID-19 crisis sub-period and the epicentre of the first wave of the COVID-19 crisis respectively.

These results confirm our initial hypothesis that connectedness between Gold price returns and cryptocurrency returns is enhanced during economic turmoil, such as the COVID 19 crisis. These results have important implications for implementing investment strategies using cryptocurrencies with hedging, diversification, and/or safe haven roles.

According to these results, virtually all cryptocurrencies in the COVID-19 sub-periods and especially Bitcoin_sv in all periods are indeed connected to Gold. Thus, Bitcoin_sv could be used to hedge Gold and other assets highly correlated with Gold and the least connected cryptocurrencies, such as Tether, Tezos and Cardano, could be used for diversification strategies or even act as a safe haven when investing in Gold. It is remarkable that Tether usually behaves the opposite of the other eleven cryptocurrencies, possibly because unlike all the other altcoins studied here, Tether is a stable coin being calibrated to maintain a unit value of one US dollar, see González et al. (2020b). This is especially evident in the level of correlation between Tether and Gold, as well as the cointegration equation, the short-run symmetry and the effect of the cumulative sum of positive and negative changes in Gold price returns on Tether returns.

There are several possible avenues for future research following on from this study. Further information concerning the connectiveness of cryptocurrencies to Gold or other financial assets can be discovered using alternative techniques such as the cross-quantilogram methodology (Han et al., 2016), the quantile cointegration model adapted to include an autoregressive distributed-lag modelling framework (Cho et al., 2015), an application of the Granger-causality technique in quantile regressions, the quantile cross spectral framework (Rehman and Vo, 2020), and the quantile cross-spectral dependence approach of Baruník and Kley (2019) and Maghyereh and Abdoh, (2020), among others. Another extension would be a study of the connectedness between the most important cryptocurrencies and other financial assets such as fixed income securities, stocks, derivatives and commodities. Yet another would be a study of the hedging effectiveness of cryptocurrencies for investments in assets highly connected with cryptocurrencies especially if the study incorporates information concerning the stability and the asymmetric response of the connectives between the cryptocurrency and the asset to be hedged. A final extension would explore the diversification or even safe haven properties of cryptocurrencies that are less connected to other financial assets where we note Tether could be a candidate for this study.

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Table 1. Top twelve Cryptocurrencies by Market Capitalization on June 30, 2020 (Total market capitalization $259.718.733.867)

Name	Market Cap	Price	Volume (24h)	Circulating Supply	Change (24h)	Starting date
Bitcoin (BTC)	$168.305.232.268	$9137,54	$16.098.660.247	18.419.106 BTC	0,02%	01/26/2015
Ethereum (ETH)	$25.159.784.008	$225,51	$6.426.887.555	111.566.279 ETH	-0,24%	03/10/2016
Tether (USDT)	$9.186.280.109	$0,999814	$19.873.390.053	9.187.991.663 USDT *	-0,19%	04/15/2017
Ripple (XRP)	$7.791.756.919	$0,176054	$1.077.226.795	44.257.803.618 XRP *	-1,10%	01/26/2015
Bitcoin Cash (BCH)	$4.095.212.870	$221,97	$1.181.224.372	18.449.313 BCH	0,01%	08/03/2017
Bitcoin SV (BSV)	$2.912.083.147	$157,85	$979.112.704	18.447.915 BSV	-0,08%	11/19/2018
Litecoin (LTC)	$2.671.799.889	$41,15	$1.611.707.923	64.927.796 LTC	-0,73%	08/24/2016
Binance Coin (BNB)	$2.394.175.344	$15,39	$155.250.698	155.536.713 BNB *	0,01%	11/09/2017
Cryto.com Coin (CRO)	$2.218.423.395	$0,125497	$64.783.134	17.677.168.950 CRO *	-0,23%	01/11/2019
EOS	$2.192.053.263	$2,35	$1.108.712.781	933.932.678 EOS *	-0,32%	07/02/2017
Cardano (ADA)	$2.146.181.729	$0,082778	$227.336.925	25.927.070.538 ADA	-0,48%	12/31/2017
Tezos (XTZ)	$1.749.520.658	$2,38	$60.420.539	734.719.311 XTZ *	-0,89%	02/02/2018

Source: Coinmarketcap website

(* Not Mineable)

Table 2. Descriptive statistics of cryptocurrency and Gold price returns

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	JB stat.	ADF stat.	PP stat.	KPSS stat.
Bitcoin	0.0026	0.0021	0.2276	-0.4973	0.0462	-0.9721	16.0815	9889***	-38.212***	-38.211***	0.1579
Ethereum	0.0028	-0.0004	0.3925	-0.5896	0.0714	-0.1113	10.8272	2744***	-33.593***	-33.645***	0.3066
XRP	0.0018	-0.0017	0.9374	-0.9965	0.1093	0.1992	26.2286	30517***	-25.397***	-46.160***	0.1539
Bitcoin_cash	-0.0005	-0.0036	0.4355	-0.5977	0.0922	0.0211	10.4516	1668***	-25.887***	-25.928***	0.0909
Theter	0.0001	0.0000	0.0453	-0.0365	0.0064	0.8783	16.0813	5785***	-24.341***	-43.723***	0.0659
Bitcoin_sv	0.0020	-0.0015	0.8979	-0.6226	0.1036	2.6613	28.9804	11634***	-21.861***	-21.772***	0.0427
Litecoin	0.0025	-0.0017	0.6070	-0.4868	0.0734	1.3747	15.9561	7002***	-29.985***	-30.030***	0.3972
EOS	-0.0007	-0.0008	0.4196	-0.5446	0.0896	-0.3558	9.2104	1210***	-27.822***	-27.813***	0.0868
Binance_coin	0.0031	0.0011	0.7683	-0.5813	0.0806	0.7369	25.0074	13217***	-26.843***	-26.845***	0.2639
Tezos	-0.0004	-0.0041	0.4084	-0.6144	0.0827	-0.7147	10.8852	1592***	-24.171***	-24.171***	0.2017
Cardano	-0.0036	-0.0035	0.3488	-0.5361	0.0743	-0.5716	9.7437	1203***	-15.989***	-27.259***	0.4541
CRO	0.0054	0.0000	0.8138	-0.5231	0.0879	2.0772	30.2607	11501***	-8.1873***	-18.978***	0.0875
Gold	0.0002	-0.0001	0.0513	-0.0515	0.0087	0.1507	7.1406	949.4***	-36.405***	-36.430***	0.3861

Notes: This table presents the descriptive statistics of daily cryptocurrency and Gold price returns over the period from January 2015 to Junes 2020. They include mean, median, minimum (Min.) and maximum (Max.) values, standard deviation (Std. Dev.) and Skewness and Kurtosis measures. JB denotes the statistic of the Jarque-Bera test for normality. The results of the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests and the Kwiatkowski *et al.* (KPSS) stationarity test are also reported in the last three columns. As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 3. Regression results of non-linear ARDL models: asymmetry and cointegration tests between 12 different cryptocurrency returns and Gold returns: whole sample period (from January 26, 2015 to June 30, 2020)

Cryptocurrencies	**PCorr**	**Coint**	**Eq**	**LAsym**	**SAsym**	**Lags $^{+}$**	**Lags $^{-}$**	**Adj. R^2**
Bitcoin	0.2967 ***	0.4927	e^{+}: 0.4988 e^{-}: 0.4796	0.0647	2.6574 ***	(2): 0.3560 *	(1): -0.5483 **	0.0153
Ethereum	0.2700 ***	0.7880	e^{+}: -1.4568 e^{-}: -1.6211	0.4450	4.2864 ***	(1): -0.8372 **	--	0.0178
XRP	0.2197 ***	20.870 ***	e^{+}: 0.1646 e^{-}: 0.1724	0.2649	1.2983	--	--	0.0897
Bitcoin_cash	0.1979 ***	1.5944	e^{+}: 0.2837 e^{-}: 0.3398	0.1729	3.1035 ***	(2): 1.1977 * (4): -1.0864 *	(1): -1.5014 **	0.0276
Tether	-0.0754	27.277 ***	e^{+}: -0.0050 e^{-}: -0.0062	0.4523	--	--	--	0.1200
Bitcoin_sv	0.1448 ***	1.6295	e^{+}: 3.2907 * e^{-}: 4.2870 *	1.5003	3.8804 ***	--	(1): -1.5015 * (3): -2.2979 ***	0.0860
Litecoin	0.1921 ***	1.4314	e^{+}: 0.0956 e^{-}: 0.1946	0.7051	3.2888 ***	--	(1): -1.3728 ***	0.0248
EOS	0.1888 ***	0.6736	e^{+}: -6.9123 e^{-}: -9.0467	0.0309	3.2299 ***	(4): -1.0491 *	(1): -2.0265 ***	0.0409
Binance_coin	0.2208 ***	0.5386	e^{+}: -0.1972 e^{-}: -0.2979	0.1606	4.5370 ***	(4): -0.9858 *	(1): -1.1096 * (3): -1.7168 ***	0.0584
Tezos	0.1 617 ***	1.3799	e^{+}: 1.6203 e^{-}: 1.6030	0.0014	4.6897 ***	--	(1): -1.7376 ***	0.0437
Cardano	0.2149 ***	3.4198 **	e^{+}: 0.5828 e^{-}: 0.9821	1.9713	4.0645 ***	--	(1): -1.2008 **	0.0646
CRO	0.1919 ***	0.2957	e^{+}: -6.3555 e^{-}: -8.1903	0.0883	3.2181 ***	--	(1): -1.5414 ** (3): -1.8242 **	0.1158

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency and Gold price returns.
PCorr refers to the Pearson's correlation coefficients defined by the null of $PCorr = 0$. **Coint** refers to the Wald test for the presence of cointegration defined by $\beta_1 = \beta_2 = \beta_3 = 0$. **Eq** shows the cointegration equation (long-run elasticities) between cryptocurrency returns and Gold price returns (GR) $R_{jt-i} = e^{+} \cdot GR^{+}_{t-i} + e^{-} \cdot GR^{-}_{t-i}$. **LAsym** refers to the Wald test for the null of long-run symmetry defined by $-\beta_2/\beta_1 = -\beta_3/\beta_1$. **SAsym** refers to the Wald test for the null of short-run symmetry defined by $\gamma_i^{+} = \gamma_i^{-}$. **Lags** $^{+}$ and **Lags** $^{-}$ show the effect of the cumulative sum of positive and negative changes (respectively) in Gold price returns for ()-lags on the rest of relevant cryptocurrencies returns.
As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.

Table 4. Regression results of non-linear ARDL models: asymmetry and cointegration tests between 12 different cryptocurrency returns and Gold returns: epicentre of the first wave of the COVID-19 sub-period (from March 1 to June 30, 2020)

Cryptocurrencies	**PCorr**	**Coint**	**Eq**	**LAsym**	**SAsym**	**Lags** $^{+}$	**Lags** $^{-}$	**Adj.** R^2
Bitcoin	0.4126 ***	4.8844 ***	e^{+}: 1.7089 ** e^{-}: 2.3980 ***	5.0363 ***	5.8332 ***	(2): -1.0995 *	(3): -1.6122 **	0.4370
Ethereum	0.4315 ***	5.9728 ***	e^{+}: 2.3073 *** e^{-}: 3.1646 ***	4.6649 **	5.3247 ***	(2): 1.7914 **	--	0.4327
XRP	0.3791 ***	5.5654 ***	e^{+}: 0.7594 e^{-}: 1.1954 *	4.4259 **	4.6386 ***	(2): 1.4945 *** (3): 1.1237 *	(3): -2.1267 ***	0.4435
Bitcoin_cash	0.3256 ***	6.2835 ***	e^{+}: 3.6271 *** e^{-}: 4.7386 ***	6.0337 **	6.0454 ***	(2): 1.4954 **	(3): -2.2949 ***	0.4675
Tether	-0.1458	5.4303 ***	e^{+}: -0.0215 e^{-}: -0.0322 *	4.7350 **	-3.8504 ***	(3): -0.0260 *	(1): 0.0512 *** (4): 0.0291 *	0.4539
Bitcoin_sv	0.3577 ***	5.6520 ***	e^{+}: 5.7982 *** e^{-}: 7.2011 ***	3.9447 **	6.1121 ***	(2): 1.7042 **	(3): -2.1619 **	0.4658
Litecoin	0.3611 ***	9.6113 ***	e^{+}: 1.9464 *** e^{-}: 2.6421 ***	8.8913 ***	4.9517 ***	(2): 1.4128 **	--	0.4223
EOS	0.3729 ***	7.4870 ***	e^{+}: 2.2222 *** e^{-}: 2.9615 ***	5.9859 ***	5.0569 ***	(2): 1.7458 **	--	0.4007
Binance_coin	0.4595 ***	4.8255 ***	e^{+}: 1.5804 * e^{-}: 2.2615 **	4.2728 **	5.3662 ***	(2): 1.5803 **	(3): -2.7058 ***	0.4843
Tezos	0.4495 ***	1.3510	e^{+}: 0.9709 e^{-}: 2.0161	1.0755	5.4549 ***	(2): 1.7401 **	(1): -2.4562 ** (3): -2.8902 ***	0.4971
Cardano	0.3799 ***	2.3729 *	e^{+}: 0.1523 e^{-}: 1.5684	1.3343	3.9983 ***	(2): 1.6547 **	(1): -2.5442 ** (3): -2.4005 **	0.4252
CRO	0.3973 ***	4.0506 ***	e^{+}: 2.1307 ** e^{-}: 3.2054 ***	4.9245 **	5.2865 ***	--	(3): -1.8665 **	0.3872

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency and Gold price returns.
PCorr refers to the Pearson's correlation coefficients defined by the null of *PCorr* = 0. **Coint** refers to the Wald test for the presence of cointegration defined by $\beta_1 = \beta_2 = \beta_3 = 0$. **Eq** shows the cointegration equation (long-run elasticities) between cryptocurrency returns and Gold price returns (*GR*) $R_{jt-i} = e^{+} \cdot GR^{+}_{t-i} + e^{-} \cdot GR^{-}_{t-i}$. **LAsym** refers to the Wald test for the null of long-run symmetry defined by $-\beta_2/\beta_1 = -\beta_3/\beta_1$. **SAsym** refers to the Wald test for the null of short-run symmetry defined by $\gamma_i^{+} = \gamma_i^{-}$. **Lags** $^{+}$ and **Lags** $^{-}$ show the effect of the cumulative sum of positive and negative changes (respectively) in Gold price returns for ()-lags on the rest of relevant cryptocurrencies returns.
As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.

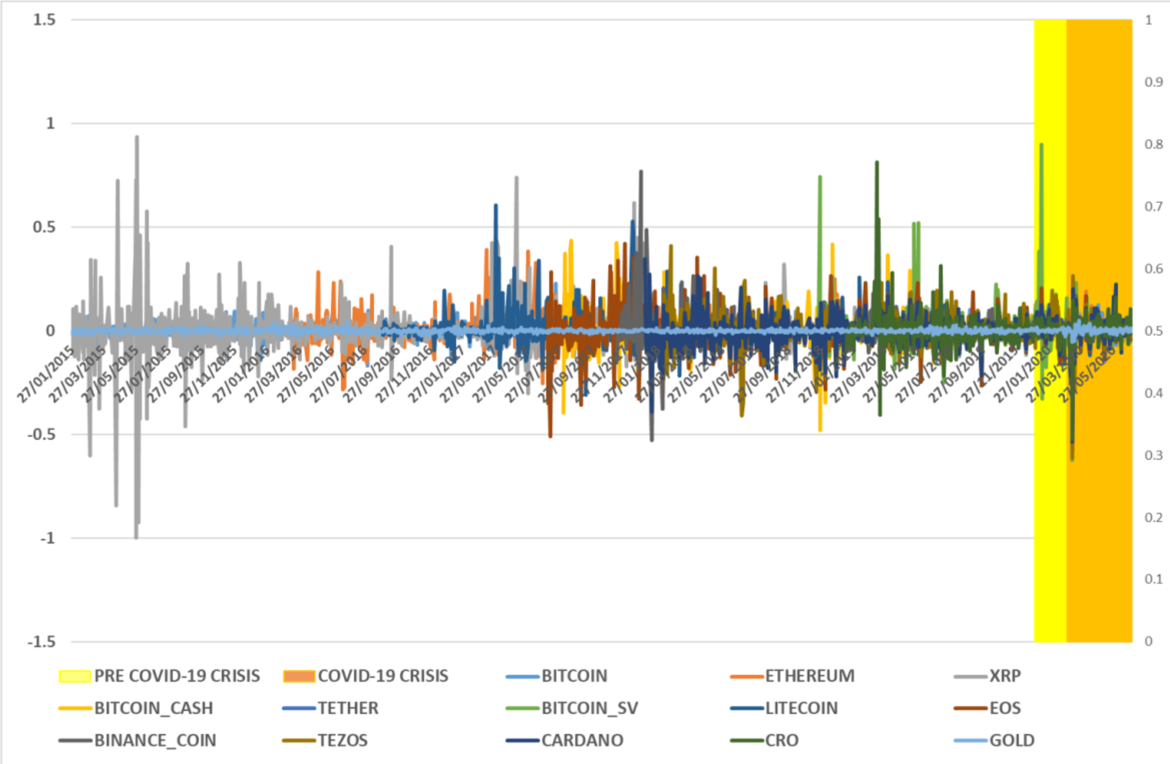
Table 5. Regression results of non-linear ARDL models: asymmetry and cointegration tests between 12 different cryptocurrency returns and Gold returns: expanded COVID-19 sub-period (from January 1 to June 30, 2020)

Cryptocurrencies	**PCorr**	**Coint**	**Eq**	**LAsym**	**SAsym**	**Lags $^{+}$**	**Lags $^{-}$**	**Adj. R^2**
Bitcoin	0.3922 ***	4.3173 ***	e^{+}: 2.1441 *** e^{-}: 2.6389 ***	3.7226 **	7.1339 ***	--	(3): -1.8804 ***	0.3825
Ethereum	0.3977 ***	3.4323 **	e^{+}: 2.0619 * e^{-}: 2.4635 *	1.7476	6.7805 ***	--	(3): -2.5446 ***	0.3855
XRP	0.3353 ***	2.7701 **	e^{+}: 2.5739 ** e^{-}: 3.0487 **	1.9330	5.8109 ***	--	(3): -1.4396 **	0.2707
Bitcoin_cash	0.2841 ***	4.8814 ***	e^{+}: 4.6740 *** e^{-}: 5.5046 ***	3.2406 *	6.2063 ***	--	(3): -2.3266 ***	0.3142
Tether	-0.1553 *	8.6891 ***	e^{+}: -0.0257 ** e^{-}: -0.0318 ***	4.1868 **	-3.7012 ***	--	(1): 0.0362 **	0.3370
Bitcoin_sv	0.2018 **	3.9310 ***	e^{+}: 5.0332 *** e^{-}: 5.8101 **	2.0051	3.9962 ***	--	(3): -2.6492 *	0.2053
Litecoin	0.3419 ***	7.8816 ***	e^{+}: 3.1799 *** e^{-}: 3.7936 ***	5.0667 **	5.9860 ***	--	--	0.3065
EOS	0.3264 ***	2.6248 **	e^{+}: 4.6556 *** e^{-}: 5.5774 ***	1.6297	5.3026 ***	--	--	0.2464
Binance_coin	0.4230 ***	2.3540 *	e^{+}: 2.2430 * e^{-}: 2.6648 *	1.3159	6.2367 ***	--	(3): 0.2239 ***	0.3753
Tezos	0.3700 ***	3.5663 **	e^{+}: 2.4613 ** e^{-}: 2.8491 *	1.3205	6.9923 ***	--	(3): -2.5894 ***	0.3791
Cardano	0.3438 ***	1.9763 *	e^{+}: 3.3337 * e^{-}: 4.2572 *	2.0429	6.2540 ***	--	(3): -1.7344 **	0.2936
CRO	0.3750 ***	3.2834 **	e^{+}: 3.7493 *** e^{-}: 4.7711 ***	2.9419 *	6.5778 ***	--	(3): -1.8408 ***	0.3301

Notes: This table reports the coefficient estimates of the NARDL model between cryptocurrency and Gold price returns.
PCorr refers to the Pearson's correlation coefficients defined by the null of $PCorr = 0$. **Coint** refers to the Wald test for the presence of cointegration defined by $\beta_1 = \beta_2 = \beta_3 = 0$. **Eq** shows the cointegration equation (long-run elasticities) between cryptocurrency returns and Gold price returns (GR) $R_{jt-i} = e^{+}\cdot GR^{+}_{t-i} + e^{-}\cdot GR^{-}_{t-i}$. **LAsym** refers to the Wald test for the null of long-run symmetry defined by $-\beta_2/\beta_1 = -\beta_3/\beta_1$. **SAsym** refers to the Wald test for the null of short-run symmetry defined by $\gamma_i^{+} = \gamma_i^{-}$. **Lags** $^{+}$ and **Lags** $^{-}$ show the effect of the cumulative sum of positive and negative changes (respectively) in Gold price returns for ()-lags on the rest of relevant cryptocurrencies returns.
As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The critical values are available in Narayan (2005), in case of small sample size.

Figure 1. Time evolution of the cryptocurrency and Gold price returns (COVID-19 crisis in the right-axis and returns in the left-axis)

Panel A: Whole sample period



Panel B: COVID-19 pandemic crisis subperiod

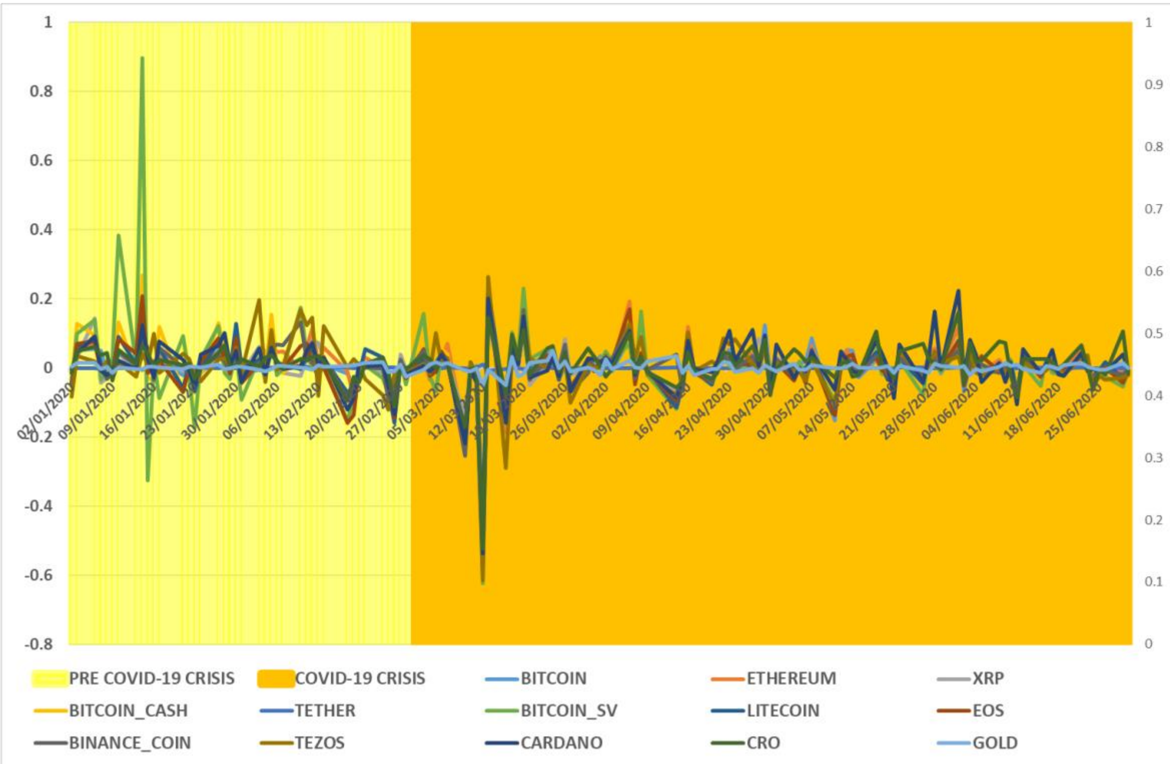
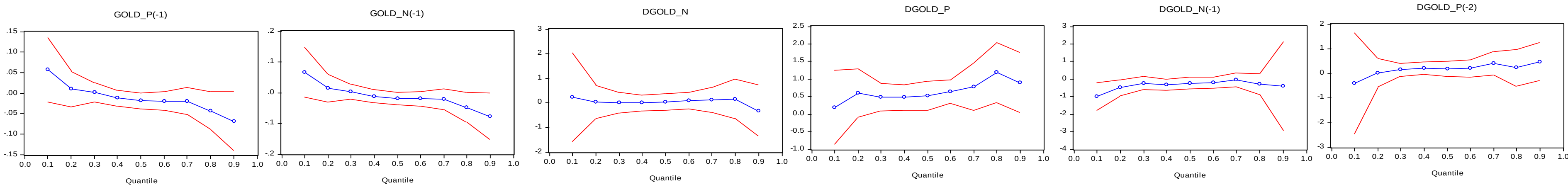
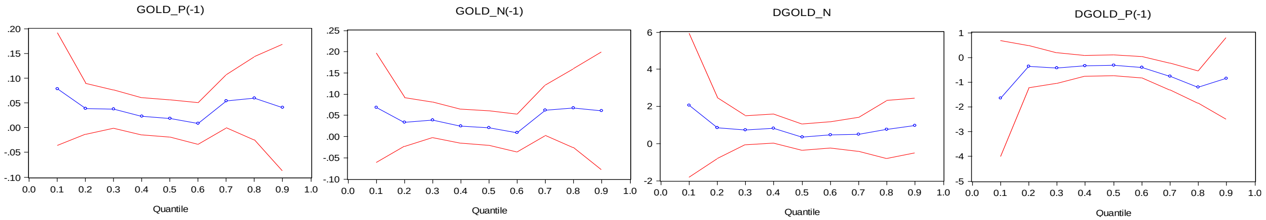


Figure 3. Analysis of the *Quantile Dependence* in the study of the asymmetric interconnection between cryptocurrency returns and changes in Gold prices

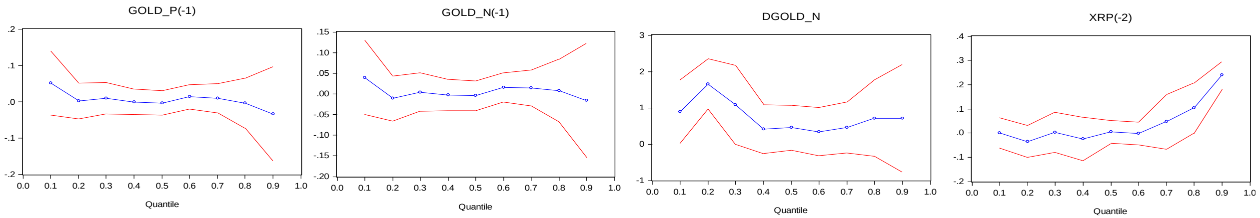
Bitcoin



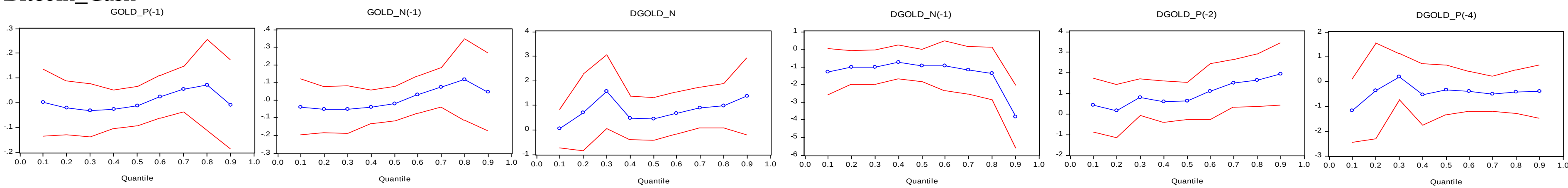
Ethereum



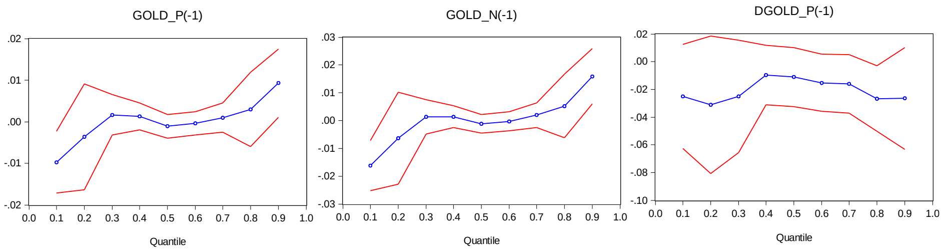
XRP



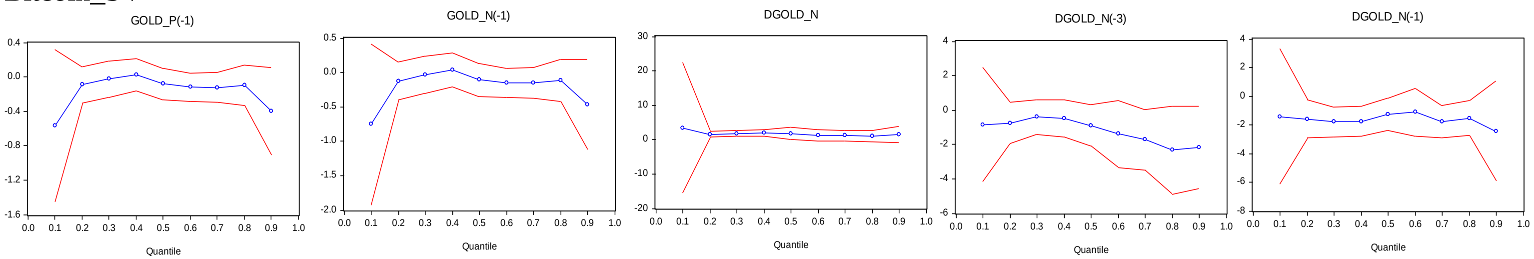
Bitcoin_Cash



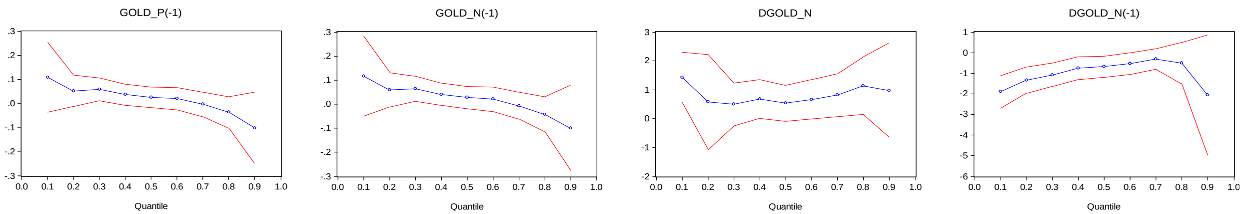
Tether



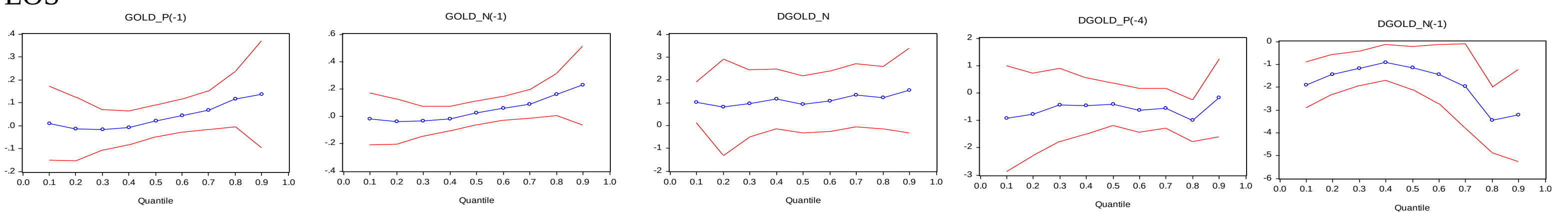
Bitcoin_SV



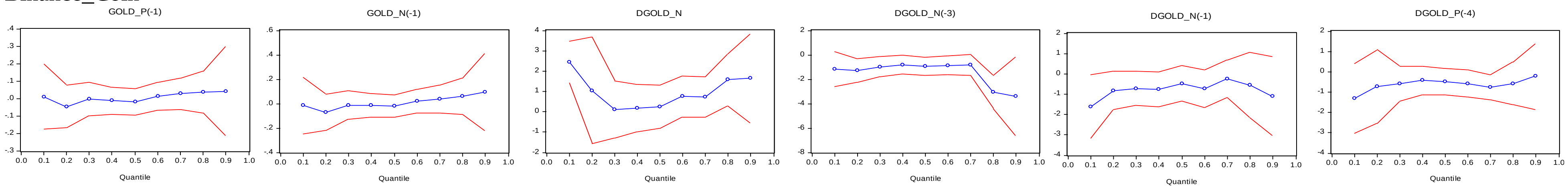
Litecoin



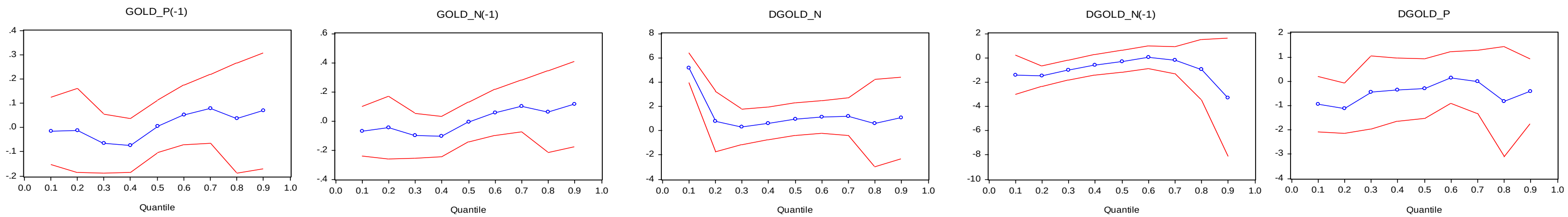
EOS



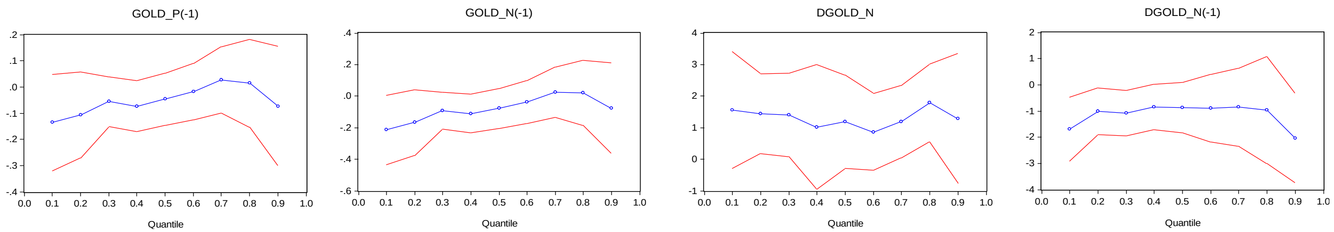
Binance_Coin



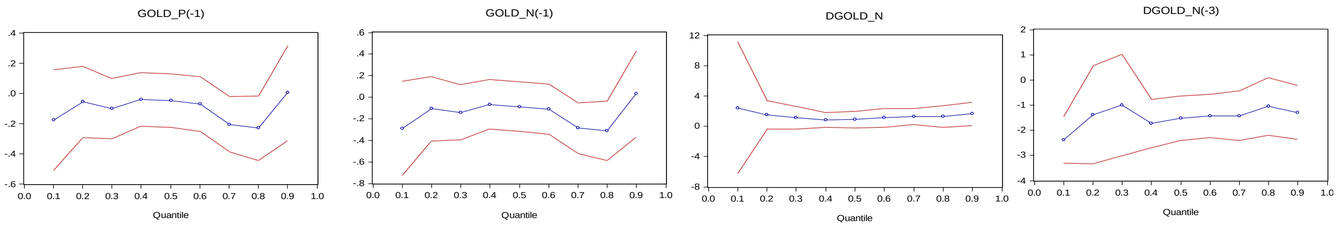
Tezos



Cardano

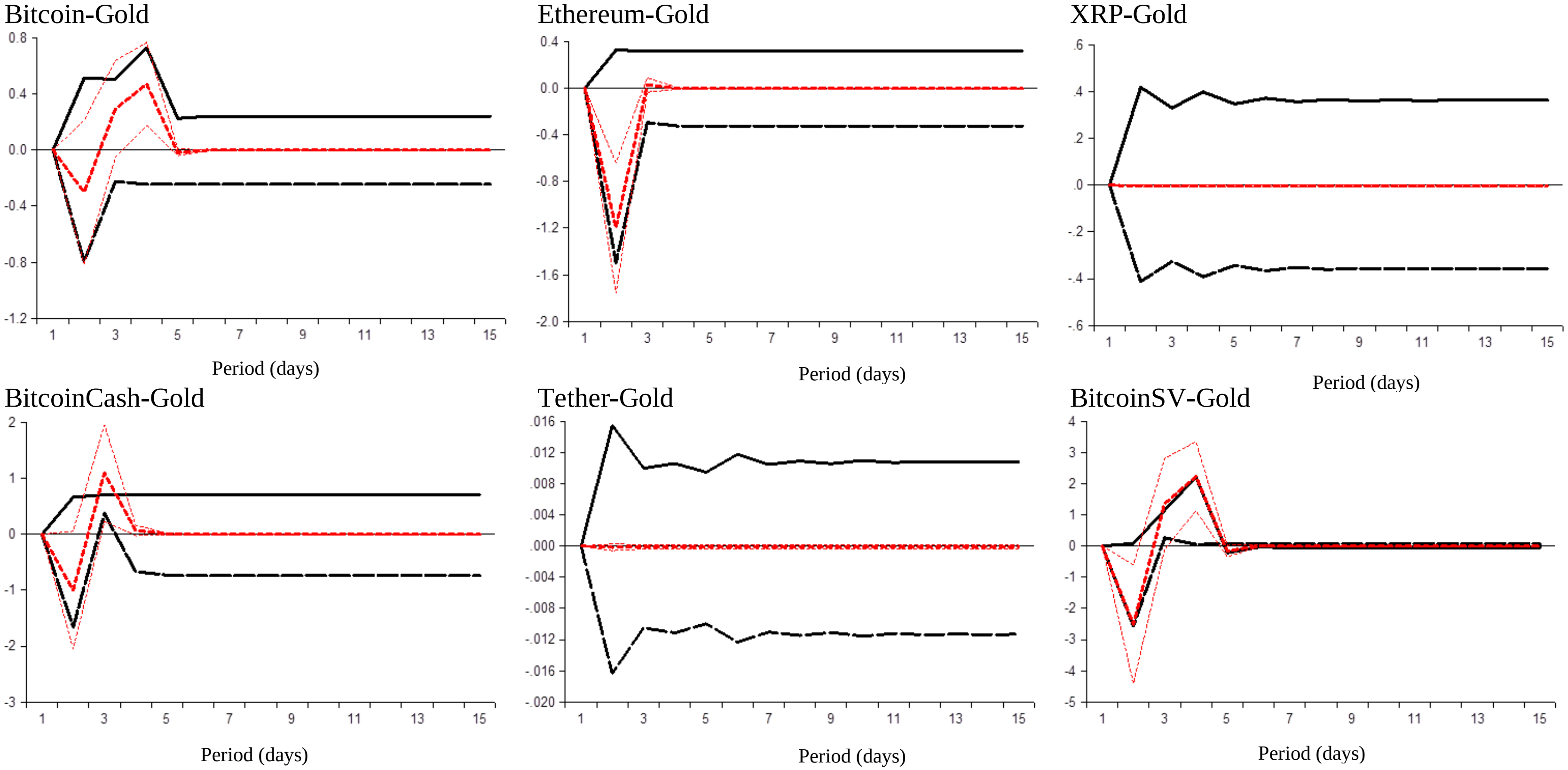


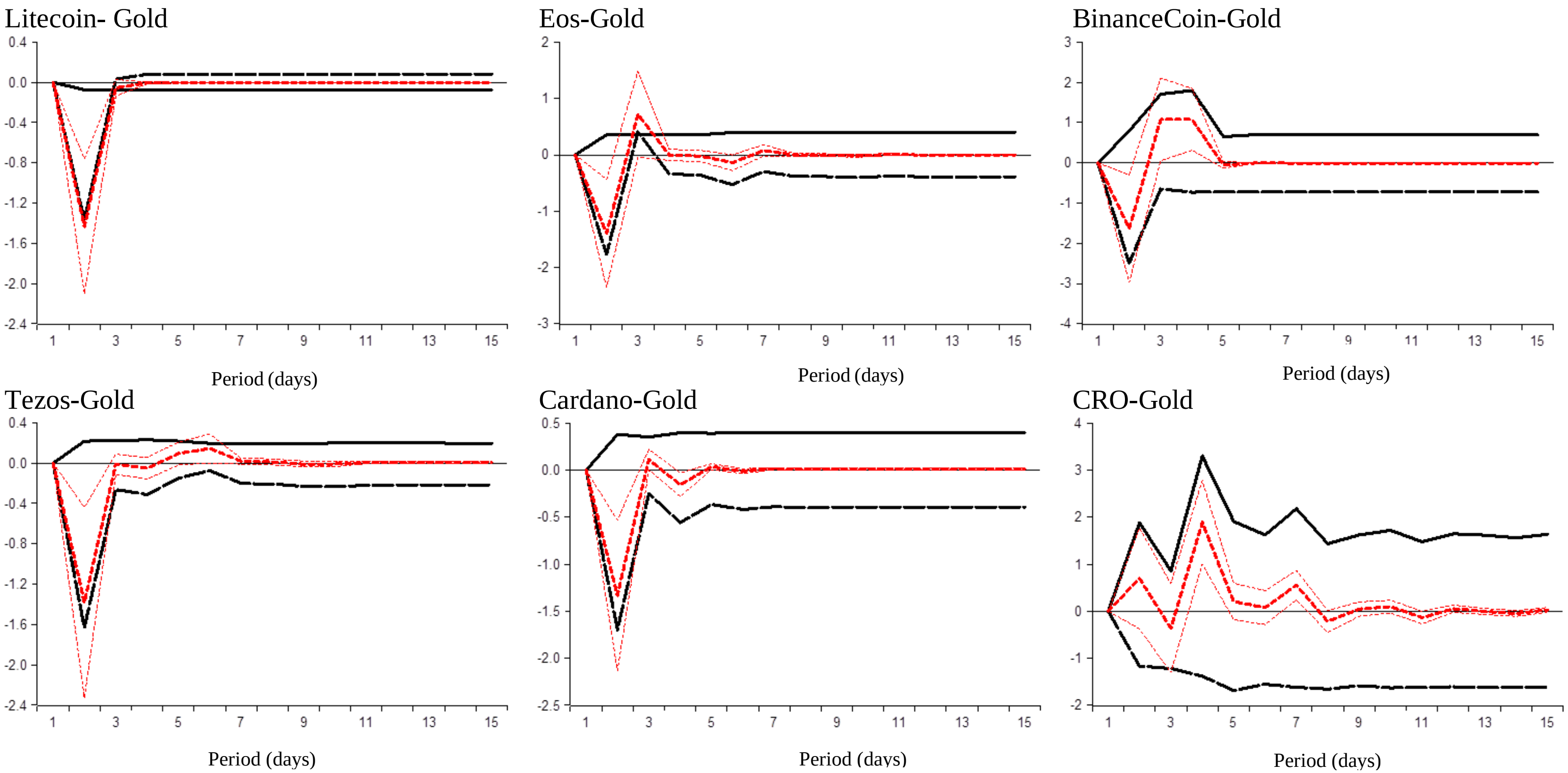
CRO



Notes: The horizontal axis shows the quantiles of the conditional distribution of cryptocurrency returns and the vertical axis the magnitude of the estimated sensitivities to fluctuations in statistically significant explanatory variables related to Gold price returns extracted from the NARDL estimates by considering cumulative sum of positive and negative changes in Gold prices (DGOLD_P and DGOLD_N), positive and negative changes (GOLD_P and GOLD_N) and potentially relevant lags () of them.

Figure 4. Asymmetric Dynamic Multipliers for the whole sample period: impact of positive and negative Gold price changes on Cryptocurrency returns





Notes: The horizontal axis shows the period (days) and the vertical axis the multiplier for positive (continuous black line) and negative (dashed black line) changes in Gold prices and the asymmetry plot (dashed red line) with 95% bootstrap confidence interval based on 1000 replications.

APPENDIX A.

Table A1. Summary table of literature review

Source	Purpose	Data/Sample period	Methodology	Key findings
First Branch				
González et al. (2020a)	To examine the connectedness between Bitcoin returns and returns of ten additional cryptocurrencies for several frequencies: daily, weekly and monthly using a NARDL approach	Daily, weekly and monthly data of Bitcoin, Ethereum, Ripple, Bitcoin_cash, Tether, Bitcoin_sv, Litecoin, EOS, Binance_coin and Tezos. Sample period from January 26, 2015 to March 7, 2020	Nonlinear Autoregressive Distributed Lag (NARDL) model	Evidence of important and positive interdependencies among cryp.tocurrencies and significant long-run relations among most of them. Strong evidence of asymmetry in the short-run. High persistence in the impact of both positive and negative changes in Bitcoin returns on most altcoins returns.
Demir et al. (2020)	To examine the asymmetric effect of Bitcoin on three altcoins	Daily dataset: Bitcoin, Ethereum, Ripple and Litecoin. Sample period from July 2015 to March 2019	Nonlinear Autoregressive Distributed Lag (NARDL) model	Evidence of asymmetric impact of Bitcoin on altcoins both in the short-run and in the long-run. In the short-run, a decrease in Bitcoin price has greater effect than an increase on the prices of altcoins
Omane-Adjepong and Alagidede (2019)	To examine market coherencies and volatility causal linkages of seven leading cryptocurrencies	Daily dataset: Bitcoin, BitShares, Litecoin, Stellar, Ripple, Monero and Dash. Sample period from May 8, 2014 to February 12, 2018.	Wavelet-based methods. Linear GARCH and nonlinear GJR-GARCH models.	First, probable diversification benefits are confined from intraweek to monthly scales for specific market pairs. Second, incremental predictive power becomes useful in unveiling the nonlinear nature of volatility feedback linkages within time-scales. Third, the level of connectedness and volatility causal linkages are found to be sensitive to trading scales and the proxy for market volatility.
Shi et al. (2020)	To analyse the correlations among six cryptocurrencies	Daily dataset: Bitcoin, Dash, Ethereum, Litecoin, Ripple, and Stellar.	Multivariate factor stochastic volatility model (MFSVM) with the	Bitcoin is mainly related to Litecoin, but Ethereum is associated with Ripple, Dash, and Stellar. Thus, the investors in the Litecoin market should monitor the

		Sample period from August 8, 2015 to January 1, 2020	Bayesian estimation procedure.	Bitcoin market meanwhile the investors on Dash, Ripple, and Stellar should monitor the Ethereum market
Kumar and Anandarao (2019)	To study the dynamics of volatility spillover across four major cryptocurrency returns	Daily dataset: Bitcoin, Ethereum, Ripple and Litecoin. Sample period from August 2015 to January 2018	IGARCH-DCC multivariate GARCH model	Possibility of turbulence in the crypto-currency markets and point towards the possibility of herding behaviour in crypto-currency markets
Ferreira et al. (2020)	To examine the serial correlation structure of six liquid cryptocurrencies with a long data record	Daily dataset: Bitcoin, DASH, Stellar, Litecoin, Monero and Ripple. Sample period from January 1, 2015 to June 30, 2018	Detrended cross-correlation (DCCA) and detrending moving-average cross-correlation (DMCA) correlation coefficients.	These six cryptocurrencies behave differently from the stock markets which are much closer to the random walk (efficient) dynamics.
Chaim and Laurini (2019)	To describe the returns and volatility dynamics of major cryptocurrencies	Daily dataset: Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Monero, NEM and Verge. Sample period from August 16, 2015 to October 31, 2018	Multivariate stochastic volatility model with discontinuous jumps to mean returns and volatility.	Long memory dependence features of cryptocurrencies are well reproduced by stationary models with jump components
Tu and Xue (2019)	To study the effect of the bifurcation of Bitcoin on its interactions with its substitute, Litecoin	Daily dataset: Bitcoin and Litecoin. Sample period from April 28, 2013 to July 31, 2018	Granger causality test and a BEKK-MGARCH model.	Bitcoin's initial bifurcation into Bitcoin and Bitcoin Cash (on August 1, 2017) has markedly weakened the market position and pricing influence of Bitcoin within cryptocurrency markets. Since bifurcation is convenient for nearly any cryptocurrency, it will likely continue to pose a risk to the cryptocurrency market as a whole

Shahzad et al. (2021)	To examine the daily return spillover among 18 cryptocurrencies under low and high volatility regimes, while considering three pricing factors and the efect of the COVID-19 outbreak	Daily dataset: Bitcoin, Ethereum, Ripple, Litecoin, Monero, Stellar, Dash, Ethereum Classic, NEM, Dogecoin, Decred, Lisk, Waves, MonaCoin, DigiByte, Steem, Siacoin and DigixDAO. Sample period from July 25, 2016 to April 1, 2020	Markov regime-switching (MS) vector autoregressive with exogenous variables (VARX) model.	Further evidence of much higher spillovers in the high volatility regime during the COVID-19 outbreak, which is consistent with the notion of contagion during stress periods.
Yousaf and Ali (2020)	To examine the return and volatility spillover between three cryptocurrencies during the pre-COVID-19 and the COVID-19 period	Intra-day data for Bitcoin, Ethereum, and Litecoin. Sample period from October 3, 2018 to April 1, 2020	VAR-AGARCH model	The hedging effectiveness is higher during the COVID19 period compared to the pre-COVID-19 period
Corbet et al. (2020)	To analyse the relationships between the largest cryptocurrencies and such time-varying realisation as to the scale of the economic shock centralised within the rapidly escalating pandemic by controlling for the polarity and subjectivity of social media data based on the development of the COVID-19 outbreak	Daily dataset: Bitcoin, Ethereum, Ripple, Bitcoin Cash, Bitcoin SV, Litecoin, Binance Coin, EOS, Tezos, Stellar, Etherum Classic, IOTA and NEM. Sample period from January, 1 2019 to March, 31 2020	Standard GARCH methodology	Evidence of significant growth in both returns and volumes traded, indicating that large cryptocurrencies acted as a store of value during this period of exceptional financial market stress. Further, cryptocurrency returns are found to be significantly influenced by negative sentiment relating to COVID-19.
Conlon and McGee (2020)	To provide a first assessment of the safe haven properties of Bitcoin during the COVID-19 bear market.	Daily dataset: Bitcoin, S&P 500. Sample period from March 21, 2019 to March 20, 2020	Two-moment value at risk (VaR).	Bitcoin does not act as a safe haven. The S&P 500 and Bitcoin move in lockstep, resulting inincreased downside risk for an investor with an allocation to Bitcoin
Second Branch				
Jareño et al. (2020)	To analyse the sensitivity of Bitcoin returns to changes in Gold price returns, US stock market returns,	Daily dataset: Bitcoin, Gold, Crude Oil, S&P500, VIX index and STLFSI index.	Quantile regression approach (QR) and Nonlinear Autoregressive	Evidence that the sensitivity of Bitcoin returns to movements in international risk factors tends to be more pronounced in extreme market conditions (bullish and

	interest rates, crude oil prices, American stock market (VIX) and Saint Louis financial stress index (STLFSI)	Sample period from August 2010 to November 2018.	Distributed Lag (NARDL) model	bearish scenarios). Moreover, there is a positive and statistically significant connectedness between Bitcoin and Gold.
Selmi et al. (2018)	To assess the roles of Bitcoin as a hedge, a safe haven and/or a diversifier against extreme oil price movements, in comparison to the corresponding roles of Gold	Daily dataset: Bitcoin, Oil and Gold. Sample period from September 13, 2011 to August 29, 2017	The quantile-on-quantile regression (QQR) approach	Both Bitcoin and Gold would serve the roles of a hedge, a safe haven and a diversifier for oil price movements. Moreover, both Bitcoin and Gold, but not oil, are assets where investors may park their cash during political and economic crisis.
Klein et al. (2018)	To analyse and compare conditional variance properties of Bitcoin, Gold and other assets.	Daily dataset: Bitcoin, Gold, Silver, Crude Oil, S&P 500, MSCI World and MSCI Emerging Markets 50 index. Sample period from July 1, 2011 to December 31, 2017	BEKK-GARCH, APARCH and FIAPARCH models	Found that cryptocurrencies such as Bitcoin are establishing themselves as an investment asset and are often named the New Gold
Guesmi et al. (2019)	To explore the conditional cross effects and volatility spillover between Bitcoin and financial indicators using different multivariate GARCH specifications	Daily dataset: Bitcoin, Gold, Oil, Euro and Chinese exchange rate, VIX, MSCI Emerging Markets and MSCI Global Market index. Sample period from January 1, 2012 to May 1, 2018	VARMA-DCC-GARCH, VARMA-DCC-EGARCH, VARMA-DCC-GARCH, VARMA-cDCC-FIAPARCH, and the VARMA-DCC-GJR-GARCH models	Affirm that hedging strategies including Bitcoin in their portfolios consisting of Gold, oil and equities reduce considerably the portfolio's risk.
Canh et al. (2019)	To study diversification capability of seven cryptocurrencies with the largest market size against risks from economic factors as oil price, Gold price, interest rate, USD strength, and S&P500	Weekly datset: Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash, and Bytecoin, Oil, Gold, S&P500, LIBOR and USD index Sample period from August 8, 2014 to June 7, 2018.	GARCH and DCC-MGARCH models	Structural breaks and ARCH disturbance in each cryptocurrency, suggesting a systematic risk within the cryptocurrency market. Furthermore, cryptocurrencies have insignificant correlations with economic factors, implying low diversification capability.

Symitsi and Chalvatzis (2019)	Frist, to analyse the statistical performance of benchmark portfolios of currencies, Gold, oil and stocks as well as a multi-asset portfolio of currencies, Gold, oil, stock, real estate and bond with respective portfolios that invest additionally in Bitcoin under four trading strategies. Second, to estimate the economic gains net of transaction costs added from Bitcoin, even in bullish and bearish cryptocurrency market conditions	Daily dataset: Bitcoin, exchange rates, Gold, Oil and stocks. Sample period from September 20, 2011 to July 14, 2017	Multivariate GARCH model.	First, statistically significant diversification benefits from the inclusion of Bitcoin which are more pronounced for commodities. Second, economic gains are not reduced after the consideration of transaction costs
Charfeddine et al. (2020)	To compare the financial properties of cryptocurrencies and investigate their dynamic relationship with major financial securities and commodities. Furthermore, they evaluate the economic and financial potential benefits of cryptocurrencies for financial investors	Daily dataset: Bitcoin, Ethereum, Gold, Crude Oil, S&P 500. Sample period from July 18, 2010 to October 1, 2018	Time-varying copula approaches and bivariate dynamic conditional correlation GARCH models	Cryptocurrencies can be suitable for financial diversification. However, cryptocurrencies are poor hedging instruments in most cases. Moreover, the relationship between cryptocurrencies and conventional assets is sensitive to external economic and financial shocks.
Bouri et al. (2018)	To examine the nonlinear, asymmetric and quantile effects of aggregate commodity index and Gold prices on the price of Bitcoin	Daily dataset: Bitcoin, Gold, bonds, S&P GSCI, MSCI World and USD index. Sample period from July 17, 2010 to February 2, 2017.	Nonlinear ARDL approach, quantile ARDL and extension of the nonlinear ARDL to a quantile framework	Possibility to predict Bitcoin price movements based on price information from the aggregate commodity index and Gold prices
Ji et al. (2019)	To examine the information interdependence among various commodities -such as energy, metals and agricultural commodities-and leading cryptocurrencies (Bitcoin,	Daily dataset: Bitcoin, Ethereum, Ripple, Stellar and Litecoin. Energy, metals (include Gold) and agricultural commodities. Sample period from August 15, 2015 to September 27, 2018	Time-varying entropy-based approach	The most important movers in the system are agricultural and energy commodities, whereas metals react the least to information flow in the system. Cryptocurrencies are integrated within broadly-defined commodity markets.

	Ethereum, Ripple, Stellar and Litecoin)			
Adebola et al. (2019)	To analyse the relationship between twelve cryptocurrencies and Gold prices	Daily dataset: Bitcoin, Bitshare, Bytecoin, Dash, Ether, Litecoin, Monero, Nem, Ripple, Siacoin, Stellar, Tether and Gold. Sample period from April 28, 2013 to March 29, 2018	Fractional integration and cointegration techniques.	Evidence of mean reversion in Gold prices and also in some of the cryptocurrencies; however, cointegration is only found in a few cases with a very small degree of cointegration in the long run relationship
Rehman and Vo (2020)	To investigate the relationship between cryptocurrencies and precious metals returns under different market conditions	Daily dataset: Bitcoin, Ethereum, Litecoin, Dash, Monero and Ripple. Gold, silver, copper, platinum, palladium and nickel. Sample period: from March 6, 2017 to August 2, 2019	Quantile cross-spectral approach.	Copper provides maximum diversification opportunities for investors with all cryptocurrencies, both under extreme market conditions, in short-run. However, in medium- and long-run, precious metals under extreme positive returns distribution are not integrated with the extreme negative cryptocurrencies returns, implying diversification opportunities for investors