



Testing for asymmetric non-linear short- and long-run relationships between crypto-currencies and stock markets

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Abstract

Using the NARDL model for the period of pandemic COVID19, we examined the asymmetric relationship between six crypto-currencies (Bitcoin, Litecoin, Bitcoin gold, Dash, Maker, and Ethereum) and seven stock market prices (S&P500, CAC40, DAX30, NIKKEI, FTSE, FTSEMIB, and SPTSX) accounting for the effects of Gold and WTI prices. In the long run, our results revealed, in most cases, a positive asymmetric relationship between digital and financial assets, suggesting a weak safe haven role for crypto-currencies. The oil price (WTI) was also found to act as a diversifier. However, for, the results revealed, in most cases, a negative asymmetric relationship between the yellow metal and the different stock prices, suggesting that gold can act as a good hedging instrument or a safe haven against stock prices in the long run. On the other hand, in the short run, the results indicate that only Bitcoin, Litecoin, and Maker have an asymmetric effect on the chosen stock prices but the effect is positive in most cases. Moreover, gold can act as a hedge/safe-haven asset in the short run. Finally, while examining the dynamic response of stock prices to the negative and positive shocks of crypto-currencies, we concluded that the majority of stock prices respond more to the negative shocks of crypto-currencies than to the positive ones.

Keywords Asymmetry · Shock transmission · COVID-19 · Cryptocurrencies · Stock prices · Gold · WTI · Safe-haven · Diversifier

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1 Introduction

Since the 2008 global financial crisis, a large number of studies have focused on how equity markets respond to such long and significant economic crises. Many Scholars have investigated the impact of the 2008 subprime mortgage crisis on the hierarchical structure of financial markets (Zhang, Gao et al., 2020), market contagion (BenMim & BenSaïda, 2019; Jin, 2016; Jin & An, 2016; Wang et al., 2017), fertilizer markets (Lahmiri, 2017b; c), crude oil markets (Junttila et al., 2018; Lahmiri, 2017a), serial correlations in stocks (Anagnostidis et al., 2016; Gao & Mei, 2019; Hasan & Mohammad, 2015; Horta et al., 2014; Lahmiri, 2015), and currency markets (Lahmiri et al., 2017a), or on shifts in the market risk (Grout & Zalewska, 2016), market connectedness (Lahmiri et al., 2017b; Rosenstein et al., 1993), and the volatility transmission (Chowdhury et al., 2019; Dimitriou et al., 2013; Karanasos et al., 2016; Lien et al., 2018; Syriopoulos et al., 2015; Xu et al., 2018).

With the appearance of the COVID-19 pandemic in Wuhan, China on December 31, 2019, and since the World Health Organization (WHO) announced this crisis as a global health disaster, the global economy has been tremendously impacted. Therefore, sales dropped, consumers changed their behavior, production was limited, businesses faced serious financial difficulties, and unemployment rates rose worldwide. Such drastic changes in the world business and economy are likely to have a major effect on the stock markets as well as on new investments, such as the crypto-currency market.

As a consequence, global financial markets were severely disrupted during this pandemic, stock markets in the United States, for example, reached four circuit breakers in two weeks, crude oil prices dropped below \$20 a barrel, setting a new drop since the beginning of the century. Most unexpectedly, the crude oil future of West Texas Intermediate (WTI), the US crude benchmark, closed at – \$37.63 a barrel on April 20, 2020, an unprecedented event that would have a major impact on policymakers and practitioners. According to; Zhang, Hu et al. (2020), financial markets around the world have responded to rising risks and changing inter-market linkages as a result of the COVID-19 global expansion. In their study, they concluded that the stock market is highly unpredictable and volatile due to the instability and economic damages caused by this pandemic. Moreover, Jeribi & Snene-Manzli (2021), Baig et al. (2020), Al-Awadhi et al. (2020), Jeribi et al. (2020), and Bader (2020) stated that the growing number of confirmed COVID-19 cases and deaths has a negative impact on stock markets.

In recent years, the exponential growth of crypto-currencies, since the inception of Bitcoin by Nakamoto (2008), has captivated the attention of investors, speculators, regulators, and academics. In fact, a large volume of research has been devoted to the pricing mechanisms of crypto-currency markets (Balcilar et al., 2017; Blau, 2017; Cheah & Fry, 2015; Cheung et al., 2015; Urquhart, 2016, 2017), the volatility drivers (Baek & Elbeck, 2015; Bouri, Das et al., 2018; Katsiampa, 2017), and the diversification ability of crypto-currencies (Bouri, Jalkh et al., 2017; Brière et al., 2015; Dyhrberg, 2016). Apart from few papers, such

as those of Corbet et al. (2018a; b) and Bouri, Das et al. (2018), most of the literature focused on crypto-currencies but neglected how they interact with the traditional economy. Therefore, uncovering such interconnectedness is essential to thoroughly assess the potential risks and advantages of crypto-currencies.

On the other hand, inter-market connectedness, as evaluated by return and volatility transmission, provides new perspectives into the global finance and has important implications for portfolio and hedging decisions. Therefore, academics and practitioners have paid a lot of attention to the interactions between stock markets and crypto-currency movements. This problem has become more critical as the market integration between conventional financial assets and crypto-currencies has increased (Bouri, Das et al., 2018).

Moreover, in 2017, crypto-currencies gained a worldwide popularity after their prices skyrocketed, prompting investors to invest a large portion of their funds into these new types of financial assets. The price hype, however, could not be sustained, and the crypto price bubble exploded at the end of 2018. This extreme volatility in the crypto-currency highlights the dangers of investing in this type of asset and for this reason, many researchers examined the volatility of crypto-currencies and the co-movement between them (Chkili, 2021; Chuen et al., 2017; Dastgir et al., 2019; Demir et al., 2018, 2020; Ghorbel & Jeribi, 2021; Gozgor et al., 2019; Omrane-Adjepong et al., 2019; Ong et al., 2015; Peng et al., 2018; Szetela et al., 2021; Yi et al., 2018).

The exponential growth of crypto-currencies has resulted in prices that are vulnerable to speculative bubbles, leading to a rise in volatility that could extend to other financial markets over time. As a consequence, clutching information transmission patterns between major stock markets and crypto-currencies is extremely important. According to Forbes and Rigobon (2002) and Gande and Parsley (2005), the information transmission processes between financial markets have been at the forefront of research since the 1990s. In fact, experts discovered that connectivity is the major key to understanding the periods of crisis, which has become an important concern, particularly following the Asian crisis. As for Diebold and Yilmaz (2009, 2012), they developed a simple quantitative measure of market interconnectedness that quickly gained traction among researchers. Volatility spillovers defined by these authors can be obtained by decomposing forecast error variance from VAR models.

The asymmetric response of volatility on stock markets is also a well-known phenomenon (Black, 1976; Christie, 1982; French et al., 1987; Pindyck, 1984), for this reason, asymmetries in shock propagation are extremely important to investors. Aside from the magnitude, direction, and duration of shocks, their sign is an important factor in determining their effects on the impacted asset. In this context, Barunik et al. (2015, 2016, 2017), suggested a measure of spillover asymmetries that combine Diebold and Yilmaz's (2009, 2012) system with the semi-variance system of Barndorff-Nielsen et al. (2010). On the other hand, while analyzing the associated volatility of 16 popular crypto-currencies, Fakhfekh and Jeribi (2019) discovered an asymmetric impact in which volatility rises more in reaction to positive shocks than in response to negative shocks, suggesting an asymmetric effect that varies from that seen in stock markets. In fact, both authors argued that the spike in volatility in reaction to positive shocks may be justified by uninformed investors' herding methods.

Also, Jeribi and Fakhfekh (2021) proved that the crude oil index (WTI) and the US indices return highlight the persistence of a negative and significant leverage effect while the crypto-currency markets present a positive asymmetric volatility effect.

Fakhfekh et al. (2021) studied the correlations between cryptocurrencies, WTI, Gold, VIX and stock markets by using multivariate GARCH models. Their findings revealed that the hedging strategy tool was neutral for the FTSE and NIKKEI stocks, however, the strategy was reversed for the American and developing markets, and this from the pre-crypto-currency crash to the during crypto-currency crash period. Also, Jeribi and Masmoudi (2021) studied the interaction between the volatilities of stock markets and crypto-currencies by using the multivariate GARCH models and they revealed that the financial markets, like the crypto-currency market, reacted to the Coronavirus pandemic with alarming volatility.

Moreover, Jeribi et al. (2021) studied the relationship dynamics of stock markets and crypto-currency returns both in the short and long run with a special focus on changes during the COVID-19 crisis period. Their results indicated that Dash and Ripple are found to be a safe haven for stock markets before the pandemic. However, crypto-currencies are found to be a safe haven for three emerging markets, such as Brazil, China, and Russia, during the pandemic COVID-19.

Despite the fact that a variety of studies have looked into the linkages between the same classes of assets (Tiwari et al., 2018) and the connectedness between different asset classes (Corbet et al., 2018a), there has been little empirical work on connectiveness between crypto-currencies and other asset classes while most of the studies do not account for the asymmetric effects. Therefore, in this paper, we examine the asymmetric relationship between crypto-currencies and stock market prices accounting for the effects of gold and WTI prices. To do so, we used the NARDL model and checked the long and short-run asymmetry effects between the digital and financial assets. Our results revealed that the stock prices are asymmetrically responding to the crypto-currency movements in both the short and long run with the long-run influence being more important. In fact, the rising movements of crypto-currencies had a greater influence on the stock prices than the declining movements, meaning that they would change the behavior of the stock prices. According to Baur and Lucey (2010),¹ the evidence on the positive relation between crypto-currencies and stock prices suggests a weak safe haven role for crypto-currencies in the long run. As for gold, the results indicated that the stock prices, in general, respond to the decreasing movements of gold more than to the increasing movements. The negative relation between stock prices and gold prices seems contradictory to the weak safe haven evidence reported in the relation between stock prices and crypto-currencies. This could lead to the conclusion that gold can act as a good hedging instrument or a safe haven against stock prices. Moreover, our results showed a weak safe haven role for the Oil index in the long run. However, we have concluded that in the short

¹ According to Baur and Lucey (2010), an asset is viewed as a hedge if it is uncorrelated or negatively correlated with another asset or a portfolio, an asset is viewed as a diversifier if it is positively but not perfectly correlated with another asset or portfolio, however, an asset is viewed as a safe-haven if it is not correlated or negatively correlated with another asset or portfolio in periods of market distress.

run, only Bitcoin, Litecoin, and Maker have an asymmetric effect on the chosen stock prices while the effect was positive in most cases. This means that these digital assets do not act as good hedging and safe-haven instruments for stock markets. On the other hand, the negative asymmetric effect of gold in the short-run dominates the positive one, improving the hedging and safe-haven role of the yellow metal. This finding supports the long-term results presented above.

While examining the multiplier impact of crypto-currencies on the stock prices, we concluded that the majority of stock prices respond more to the negative crypto-currency shocks than to the positive ones. Finally, our study proves that crypto-currencies and commodities (gold and WTI) are significant driving factors for the stock market prices.

Then, the remainder of this paper is organized as follows. Section 2 reviews the relevant literature, Sect. 3 discusses the data and methodology, Sect. 4 presents the empirical results, and Sect. 5 concludes the paper.

2 Literature review

In fact, many studies have investigated the different aspects of crypto-currencies and their connections to other financial assets. In this context, Bouri, Das et al. (2018) investigated the connection between Bitcoin and conventional financial assets by using a smooth transition VAR-GARCH-in-mean model. Their results indicated that Bitcoin's returns are closely related to most of the other assets, particularly commodities, suggesting that the Bitcoin market is not completely isolated. On the other hand, Baumöhl (2019) discovered a negative correlation between Forex and crypto-currencies and proposed that investing in these assets could provide diversification advantages to investors. As for Matkovskyy and Jalan (2019), they used the regime-switching skew-normal model to investigate the contagion effect between five stock indexes and Bitcoin markets and found major contagion effects from the financial markets to the Bitcoin ones. For his part, Yang (2020) discovered that Taiwan's stock market and Bitcoin have a significant nonlinear relationship. On the other hand, using the asymmetric DCC and wavelet coherence approaches, Umar et al. (2020) examined the connectedness between five crypto-currencies, namely Bitcoin, Ethereum, Ripple, Bitcoin Cash, and Ethereum Operating System, and five major stock markets, such as NYSE, NASDAQ, SSE, Nikkei 225, and Euronext NV. In fact, their results showed an important time-varying conditional association between the plurality of crypto-currencies and the stock market indices, indicating that negative shocks play a bigger role than positive shocks with the same dimension. As for Sami and Abdallah (2020), they examined the effect of crypto-currency market on the Gulf stock market and concluded that both markets substitute for investors (i.e. the crypto market has a disturbing influence on stock market indexes). This means that an increase in the crypto-currency returns is associated with a decline in the stock market.

For their part, Ciaian et al. (2016) revealed that the price of Bitcoin is not responsive to long-term macro-financial events, however, Li and Wang (2017) discovered a

substantial association between Bitcoin's price and movements in economic fundamentals in both the short and long run.

Moreover, Bouri, Gupta et al. (2018) investigated the impacts of the aggregate commodities index and gold prices on Bitcoin prices, and their findings suggested that price data from the aggregate commodities and gold price indexes might be used to forecast Bitcoin price changes. To test Bitcoin's safe-haven characteristic against assets, Bouri, Jalkh et al. (2017) and Bouri, Molnár et al. (2017) employed quantile dummies within a DCC approach and showed that, respectively, Bitcoin operates as a safe haven for energy commodities and against weekly severe down moves in Asian equities. Meanwhile, Corbet et al. (2018a) examined the relationship between three crypto-currencies (Bitcoin, Ripple, and Litecoin) and a variety of other financial assets, suggesting that crypto-currencies are rather isolated from other markets. In a similar study, Trabelsi (2018) discovered no compelling spillover impact between crypto-currencies and stocks. Moreover, Kostika and Laopodis (2019) found that crypto-currencies have neither short nor long-term stochastic trends with the stock markets. As for Zeng et al. (2020), they discovered a poor connection between Bitcoin and the conventional financial assets they studied. On the other hand, using the ARDL bound testing model, Bouoiyour and Selmi (2015) revealed that Bitcoin exhibits unfavorable speculative behavior, suggesting that it is not a safe haven asset. Furthermore, Bouri, Gupta et al. (2017) discovered a negative association between the volatility of Bitcoin and the US implied volatility index (VIX) while Baur et al. (2015) demonstrated that Bitcoin is an investment tool and addressed its position as a good diversifier (i.e. uncorrelated with the conventional assets). Using weekly data for the period ranging from 2010 to 2013, Brière et al. (2015) discovered that Bitcoin has a low association with conventional assets and that it can be used as a compelling tool of diversification, given its extremely high average return and volatility.

Using a guided acyclic graph technique and while concentrating on the incorporation of the Bitcoin market into the world financial system, Ji et al. (2018) discovered a relatively poor association between Bitcoin and equity markets, including the yellow metal market. On the other hand, Aslanidis et al. (2019) examined the conditional correlation performance of four main crypto-currencies, namely Bitcoin, Monero, Dash, and Ripple, stock (S&P500) and bond indices, and gold prices. Their findings showed that the analyzed crypto-currencies are positively correlated while the correlation between the crypto-currencies and the conventional financial assets is negligible. Using fractional integration techniques, Gil-Alana et al. (2020) examined the features of six main crypto-currencies and their bilateral connections with six stock market indices. Their results showed that there is no co-integration between the six crypto-currencies studied neither between the crypto-currencies and the stock market indexes, implying that crypto-currencies are decoupled from conventional financial and economic assets.

Using a novel dependence approach, Maghyereh and Abdoh (2021) investigated the return dependency between Bitcoin and the stock market returns. In fact, they found a high return dependency between Bitcoin and the financial markets in the long run and that such dependence dramatically decreases from yearly to monthly investment horizons. Besides, Bitcoin's right-tail dependency with the US stock

exchange is considered the greatest when compared to other stock markets. These authors also used a wavelet-coherence analysis to withdraw information on the time-varying and time–frequency dynamics of Bitcoin and the stock markets co-movements. In fact, their findings showed that the co-movement between the Bitcoin and the US stock market is positive, while it is negative for other stock markets at some frequencies and time intervals. For their part, using the Bayesian panel VAR model, Huang et al. (2021) investigated the function of Bitcoin as a safe haven against the unfavorable fluctuations of stock and bond assets in five major economies during the COVID-19 bear market and they discovered that Bitcoin contributes to the diversification advantages and/or risk reduction both inside and across the boundaries in each target economy while its position, as a hedge against conventional assets, differs among economies. The authors also showed that with the exception of the United States, the COVID-19 pandemic has changed the status of Bitcoin in different segmented markets.

As for Kurka (2019), the author examined the asymmetric transmission mechanisms of shocks between traditional asset classes and crypto-currencies. The author's findings indicated that there exists no unconditional connection between crypto-currencies and conventional assets. On the other hand, the research revealed times of significant shock transmission between Bitcoin and conventional properties. This discovery casts doubt on the capacity of Bitcoin to act as a hedge in counter to financial assets and demonstrates how the market disruptions can spread from crypto-currencies to the conventional economy. Baur and Dimpfl (2018) studied the asymmetrical volatility consequences of 20 distinct cryptocurrencies. They discovered that only positive shocks boost volatility, showing an asymmetric impact that is different from the one observed in financial markets. Furthermore, by applying quantile-based connectedness measures for seven major crypto-currencies, Bouri et al. (2021) found that the connectedness measures in the left and right tails of the conditional distribution are much higher than those in the mean and median. This means that with both positive and negative shocks, return connectedness increases with the shock size, implying that return shocks circulate more intensely during extreme events than during relaxed times. Although this finding demonstrates the system's instability in the face of severe events, like the COVID-19 pandemic, it also highlights the need to go beyond mean-based connectedness measures to comprehend the return connectedness in the face of extreme negative and positive shocks.

3 Data and methodology

3.1 Data

Therefore, the aim of this paper is to examine the asymmetric relationship between crypto-currencies and stock market prices accounting for the effects of gold and WTI prices. Our data consists of 571 observations on closing prices for seven stock market indices (S&P500, CAC40, DAX30, NIKKEI, FTSE, FTSEMIB, and SPTSX) and six crypto-currencies (Bitcoin, Litecoin, Bitcoin gold, Dash, Maker, and Ethereum). The database was collected from the Coin Market Cap, and

Table 1 Descriptive statistics

	Mean	Median	Max	Min	Std. dev.	Skew	Kurt	JB	Prob
S&P500	8.036	8.021	8.249	7.713	0.101	-0.019	2.554	4.732	0.093
CAC40	8.556	8.577	8.717	8.230	0.099	-0.528	2.621	29.919	3.185e-07
NIKKEI	7.669	7.644	7.928	7.413	0.098	0.534	2.881	27.448	1.095e-06
DAX30	9.400	9.418	9.550	9.040	0.093	-0.966	3.767	102.555	5.374e-23
FTSE	8.806	8.841	8.947	8.515	0.105	-0.434	1.826	50.570	1.044e-11
FTSEMIB	9.925	9.934	10.145	9.608	0.106	-0.469	2.682	23.299	8.719e-06
SPTSX	9.682	9.700	9.800	9.326	0.075	-1.437	5.620	358.639	1.325e-78
BITCOIN	8.896	8.985	9.473	8.131	0.214	-0.864	2.646	73.827	9.303e-17
DASH	4.455	4.392	5.185	3.685	0.328	0.169	2.721	4.575	0.101
BITCOIN GOLD	2.263	2.210	3.446	1.595	0.362	1.394	5.364	317.138	1.361e-69
LITECOIN	4.323	4.343	5.450	3.155	0.529	-0.080	2.342	10.863	0.004
ETHEREUM	5.206	5.200	5.819	4.649	0.258	0.001	2.191	15.508	0.000
MAKER	6.214	6.251	6.970	5.332	0.233	-0.924	4.656	146.141	1.843e-32
GOLD	7.370	7.356	7.631	7.146	0.141	-0.060	1.689	41.052	1.217e-09
WTI	3.849	3.965	4.193	2.068	0.307	-2.214	9.290	1403.191	1.999e-305

Datastream. The study period ranges from 01 January 2019 to 23 February 2021, noting that the period also covers the COVID-19 crisis. Even though the study on a period of crisis may not yield good results, we chose to work on that period because there was a revival of the stock market indexes and crypto-currencies also of the oil (WTI) and the gold prices since the date of the announcement of the appearance of vaccines² (see the graphs from 1 to 15).

The descriptive statistics of cryptocurrencies, stock market indices, and asset returns are presented in Table 1.

From Table 1, the results indicate that all the series have a positive mean value where the highest mean value is taken by the Italian stock market index (FTSEMIB), and the lowest by the Bitcoin gold. Moreover, the results showed that all the variables, excepting the S&P500 and Dash, have a non-normal and asymmetric distribution. Therefore, the crypto-currency distribution is negatively asymmetric for Bitcoin, Litecoin, and Maker but positively skewed for the others. As for gold and WTI, the distribution is asymmetric and spread to the left.

In fact, all the variables have a positive Kurtosis. Here, we are talking about the leptokurtic distribution which is more observed in the financial market where the ends are thicker than the normal distribution, which explains the frequent existence of abnormal values. On the other hand, among all the crypto-currencies, Bitcoin has the highest average and the lowest volatility. Furthermore, Maker and Bitcoin gold are less stable than the other crypto-currencies where their Kurtosis value is higher

² There is a significant drop in the appearance of the pandemic; this fall is mainly explained by the total containment in all countries of the world. Then, we see a good recovery especially after the announcement of the production of certain vaccines.

than three. Therefore, all the crypto-currencies, excepting Dash, as evidenced by the Jarque–Bera normality test, are far from the normal distribution.

Table 2 presents the correlation matrix between the variables. The results show that Bitcoin is positively correlated with all stock markets except for the FTSE, then, Dash is positively correlated with all stock markets except for the S&P500 and NIKKEI while Bitcoin gold is negatively correlated with all stock markets except for FTSE.

On the other hand, Litecoin is positively correlated with all stock markets except for the S&P500 while Maker is positively correlated with all stock markets except for CAC40, FTSE, and FTSEMIB; and finally, Ethereum is positively correlated with all stock markets.

Regarding the stock market indices, Table 2 shows that they are positively correlated with WTI. However, the results showed a negative correlation with gold except for the S&P500, NIKKEI, and DAX30. Lastly, gold shows a negative correlation with crypto-currencies except for Bitcoin and Maker, whereas WTI is positively correlated with all crypto-currencies except for Bitcoin and gold with which it is negatively correlated.

3.2 Empirical methodology

The first step in the econometric methodology is the unit root test, which helps determine the order of integration of a series due to the presence of a turning point in the price dynamics and also econometrics in selecting the model and the estimation method to use. For this purpose, we have used the breakpoint unit root test (Perron, 1990), which helped for one structural break in the data. In fact, the results of this step are shown in Table 3 where we found that some of the variables are stationary in level while others are stationary in difference. This means that the results of the stationarity test show that there is a mixture of $I(1)$ and $I(0)$ of the underlying regressions.

Moreover, in this paper, we adopt the non-linear ARDL model of Pesaran et al. (2001)³ to establish the long-term relationship between the stock market prices and crypto-currencies. The advantage of using this model is that it employs only a single reduced form equation. On the other hand, the linear ARDL model permits to simultaneously obtain the long-term relationship and the short-term dynamics, however, under an asymmetric effect, the non-linear ARDL model allows giving the negative and positive long-term effects (respectively short-run).

Before moving on to the presentation of the non-linear ARDL model and the estimation results, we mention that we have observed in the Box graph (from graph 16 to graph 24) that there are outliers for several variables, which can make our results non-significant or unreliable. For this reason, this problem has been corrected.⁴

³ Is the extension of Auto Regressive Distributed Lag (ARDL) model of Pesaran and Shin (1995, 1999), Pesaran et al. (1996) and Pesaran (1997).

⁴ The first step is to detect the outliers using extremes or box plot graph by their commands in STATA. Then, we treat the outliers using winsorization and trimming outlier (we have to use the winsor2 command in STATA).

Table 2 The correlation matrix

	SP500	CAC40	NIKKEI	DAX30	FTSE	FTSEMIB	SP/TSX	BITCOIN DASH	BITCOIN GOLD	LITE-COIN	MAKER	GOLD	WTI	
SP500	1.000													
CAC40	0.2121	1.000												
NIKKEI	0.8056	0.3861	1.000											
DAX30	0.5859	0.8053	0.7845	1.000										
FTSE	-0.1958	0.8652	-0.0577	0.4748	1.000									
FTSEMIB	0.2379	0.9885	0.4195	0.824	0.8327	1.000								
SPTSX	0.4629	0.8873	0.6398	0.93	0.662	0.8938	1.000							
BITCOIN	0.455	0.2167	0.4009	0.3555	-0.1082	0.2244	0.207	1.000						
DASH	-0.1227	0.4522	-0.1241	0.2618	0.5366	0.4136	0.3327	0.2235	1.000					
BITCOIN GOLD	-0.3848	-0.1816	-0.266	-0.2572	0.0436	-0.1343	-0.2092	-0.6524	-0.2625	1.000				
LITECOIN	-0.0314	0.0785	0.0341	0.0455	0.2252	0.0628	0.1594	-0.6251	0.2314	0.4364	1.000			
ETHEREUM	0.403	0.2024	0.1578	0.2034	0.0493	0.1951	0.1844	0.7389	0.5912	-0.5555	-0.1833	1.000		
MAKER	0.1369	-0.0949	0.0974	0.0355	-0.029	-0.0972	0.0385	-0.1799	0.1513	0.3803	0.5638	0.022	1.000	
GOLD	0.7292	-0.3374	0.5938	0.1765	-0.721	-0.2949	-0.0477	0.541	-0.3413	-0.3817	-0.3332	0.022	1.000	
WTI	0.0733	0.3419	0.0472	0.1985	0.4725	0.2831	0.3101	-0.2393	0.3852	0.1288	0.6288	0.5206	-0.358	1.000

Table 3 Break-point unit root test

Series	Level	P-value	Difference	P-value	Integration order
SP500	-3.817	(0.2489)	-32.191*	(<0.01)	I(1)
CAC40	-4.178	(0.2704)	-26.011*	(<0.01)	I(1)
NIKKEI	-5.41*	(<0.01)	-	-	I(0)
DAX30	-4.232	(0.2403)	-29.728*	(<0.01)	I(1)
FTSE	-5.67*	(<0.01)	-	-	I(0)
FTSEMIB	-4.64	(0.0901)	-25.850*	(<0.01)	I(1)
SPTSX	-4.408	(0.164)	-33.005*	(<0.01)	I(1)
Bitcoin	-3.700	(0.5646)	-29.796*	(<0.01)	I(1)
Dash	-3.009	(0.9085)	-23.777	(<0.01)	I(1)
Monero	-3.850	(0.6184)	-30.070*	(<0.01)	I(1)
Bitcoin gold	-4.042	(0.3459)	-29.191*	(<0.01)	I(1)
Ethereum	-3.048	(0.8966)	-31.017*	(<0.01)	I(1)
Litecoin	-3.668	(0.5849)	-25.272*	(<0.01)	I(1)
Maker	-3.827	(0.4827)	-32.300*	(<0.01)	I(1)
Ripple	-4.336	(0.3177)	-24.887*	(<0.01)	I(1)
GOLD	-3.856	(0.4644)	-24.666*	(<0.01)	I(1)
WTI	-5.485*	(<0.01)	-	-	I(0)

* indicates that the series are stationary in 1% level

3.3 The NARDL model

Following the arguments in subsection 3.2, we adopt the Non-linear Autoregressive Distributed Lag Model (NARDL). This model allows considering data series with mixed integration orders and it also allows modeling in separate forms the short and long-run effects of the explanatory variables.

The empirical model to estimate represents the stock prices in time t as follows:

$$y_t = f(X_t, GOLD_t, WTI_t) \tag{1}$$

where y_t represent the dependent variable (the different stock prices), X_t represents the cryptocurrencies.

The NARDL model of Pesaran et al., (2001) allows accounting for the positive and negative effect of the explanatory variables and it is written as follows:

$$\Delta y_t = \alpha_0 + \sum_{i=1}^p \alpha_1 \Delta y_{t-i} + \sum_{i=0}^q \alpha_2 \Delta X_{t-i}^+ + \sum_{i=0}^q \alpha_3 \Delta X_{t-i}^- + \rho y_{t-1} + \varphi_1^+ X_{t-1}^+ + \varphi_2^- X_{t-1}^- + \mu_t. \tag{2}$$

The question to ask is as follows: does the impact of the explanatory variables on the dependent variable have the same magnitude of changes in the two cases (positive and negative)? If the impact has the same magnitude of changes this means that the relationship is symmetric, if the impact has a different magnitude of changes this means that the relationship is asymmetric. The NARDL model

denotes the positive partial sum of changes in X by X^+ and the negative partial sum of changes in X by X^- .

The partial sum for increases and decreases can be represented as follows:

$$X_t^+ = \sum_{j=1}^t \Delta X_j^+ = \sum_{j=1}^t \max(\Delta X_j, 0)$$

$$X_t^- = \sum_{j=1}^t \Delta X_j^- = \sum_{j=1}^t \min(\Delta X_j, 0).$$

The asymmetric error-correction form of our empirical model as proposed by Pesaran et al. (2001) and Shin et al. (2014) is as follows:

$$\begin{aligned} \Delta y_t = & \alpha_0 + \sum_{i=1}^p \alpha_1 \Delta y_{t-i} + \sum_{i=0}^q \alpha_{21} \Delta X_{t-i}^+ + \sum_{i=0}^q \alpha_{22} \Delta X_{t-i}^- \\ & + \sum_{i=0}^q \alpha_{31} \Delta WTI_{t-i}^+ + \sum_{i=0}^q \alpha_{32} \Delta WTI_{t-i}^- + \sum_{i=0}^q \alpha_{41} \Delta GOLD_{t-i}^+ \\ & + \sum_{i=0}^q \alpha_{42} \Delta GOLD_{t-i}^- + (\varphi_{11}^+ X_{t-1}^+ + \varphi_{12}^- X_{t-1}^-) \\ & + (\varphi_{21}^+ WTI_{t-1}^+ + \varphi_{22}^- WTI_{t-1}^-) + (\varphi_{31}^+ GOLD_{t-1}^+ + \varphi_{32}^- GOLD_{t-1}^-) + \rho y_{t-1} + \mu_t. \end{aligned} \quad (3)$$

The detection of short and long-run asymmetry can be obtained by the Wald test. A Wald F-statistics assume the hypothesis test of joint significance where:

$$\begin{cases} H_0 : \rho = \varphi_{11}^+ = \varphi_{12}^- = \varphi_{21}^+ = \varphi_{22}^- = \varphi_{31}^+ = \varphi_{32}^- = 0 \Rightarrow \text{non cointegration} \\ H_a : \rho \neq \varphi_{11}^+ \neq \varphi_{12}^- \neq \varphi_{21}^+ \neq \varphi_{22}^- \neq \varphi_{31}^+ \neq \varphi_{32}^- \neq 0. \end{cases}$$

If the F-statistics is greater than the critical values (Pesaran et al., 2001), the decision is the rejection of the null hypothesis and this means that a long-run relationship can exist.

$$\begin{cases} H_0 : \rho = 0 \\ H_a : \rho < 0. \end{cases}$$

According to Banerjee et al. (1998), if the null hypothesis is rejected the long-run relationship can exist in the presence of an asymmetric effect.

Wald proposed a hypothesis test for the symmetric or asymmetric effect as follows:

We calculate the coefficient of long-run asymmetry:

$$\begin{cases} \frac{-\varphi_{12}^+}{\rho} = L_{M_1^+} \\ \frac{-\varphi_{22}^-}{\rho} = L_{M_1^-} \end{cases}$$

The hypothesis test for the long-run effect is:

$$\begin{cases} H_0 : \frac{-\varphi_{11}^+}{\rho} = \frac{-\varphi_{12}^-}{\rho} \Rightarrow \text{symmetric effect of } X_{t-1} \text{ on } y_t \text{ in long-run} \\ H_a : \frac{-\varphi_{11}^+}{\rho} \neq \frac{-\varphi_{12}^-}{\rho} \Rightarrow \text{asymmetric effect of } X_{t-1} \text{ on } y_t \text{ in long-run.} \end{cases}$$

The hypothesis test for the short-run effect is:

$$\begin{cases} H_0 : \frac{-\alpha_{21}^+}{\alpha_1} = \frac{-\alpha_{22}^-}{\alpha_1} \Rightarrow \text{symmetric effect of } X_{t-1} \text{ on } y_t \text{ in short-run} \\ H_a : \frac{-\alpha_{21}^+}{\alpha_1} \neq \frac{-\alpha_{22}^-}{\alpha_1} \Rightarrow \text{asymmetric effect of } X_{t-1} \text{ on } y_t \text{ in short-run.} \end{cases}$$

The Same hypothesis test goes for the short and long-run effect of Gold and WTI on stock prices.

4 Estimation results

We start analyzing first, the long- term asymmetric effect of the explanatory variables on the dependent variables, then, the short term effect and the error correction term.

The obtained results are reported in Tables 4, 5, 6, 7, 8, 9, 10, 11 and 12 respectively. We also used the Wald test to examine the short and long-term asymmetry hypothesis. From the obtained results, we can draw many general conclusions. First, the existence of a co-integration relationship between all the variables for the different estimated models because the coefficients of the long-term relationship are different from zero. Second, we can confirm the non-linearity relationship between the dependent variables and the explanatory ones, where the F-statistic (from Tables 6, 7, 8, 9, 10, 11 and 12) appears to be significant, which indicates that the different stock prices are non-linearly co-integrated with crypto-currencies, gold, and WTI. Finally, as it is shown in Tables 4 and 5, we can confirm the existence of short and long term asymmetry effects of the different stock prices and the explanatory variables where we have obtained different coefficients of increasing and decreasing effects by the Wald test, so the null hypothesis of short and long term symmetric fluctuations is rejected.

Table 4 The Long-run asymmetry test of Wald

	S&P500	CAC40	DAX30	FTSE	FTSEMIB	NIKKEI	SPTSX
Bitcoin							
+	-0.012811 (0.8015)	0.102989 (0.1796)	0.041760 (0.6453)	0.074073 (0.1360)	0.094525 (0.3513)	0.049517 (0.5860)	0.017758 (0.7557)
-	-0.047125 (0.5468)	-0.007703 (0.9471)	-0.023617 (0.8642)	0.004824 (0.9487)	0.007892 (0.9590)	-0.071459 (0.5910)	-0.026845 (0.7515)
Litecoin							
+	0.022287 (0.741)	0.052112 (0.6540)	0.063236 (0.5850)	0.008763 (0.8997)	0.01608 (0.9245)	-0.017257 (0.8977)	0.043377 (0.5199)
-	0.034347 (0.3842)	-0.008737 (0.8979)	0.031131 (0.6409)	-0.01664 (0.6840)	0.052716 (0.6039)	0.050784 (0.4982)	0.058706 (0.1414)
Bitcoin gold							
+	-0.009356 (0.8683)	-0.091439 (0.2985)	-0.04233 (0.6598)	-0.06645 (0.1761)	-0.08731 (0.4933)	-0.031028 (0.7623)	-0.021088 (0.7113)
-	-0.057174 (0.4627)	-0.126403 (0.2750)	-0.078581 (0.5402)	-0.10865 (0.0977)	-0.150897 (0.3765)	-0.035820 (0.7912)	-0.034560 (0.6507)
Maker							
+	0.056289 (0.5737)	0.124405 (0.3765)	0.121166 (0.5179)	0.093679 (0.2719)	0.062298 (0.7839)	0.043769 (0.8278)	0.110776 (0.3106)
-	0.003377 (0.9677)	-9.30 ^{e-06} (0.9999)	0.126983 (0.4418)	-0.00061 (0.9934)	0.020615 (0.9149)	0.023613 (0.8883)	0.086533 (0.3708)
Dash							
+	-0.037943 (0.4746)	0.020877 (0.7893)	-0.016178 (0.8515)	0.009455 (0.8480)	-0.063311 (0.6371)	-0.048383 (0.5240)	0.029569 (0.4780)
-	-0.084409 (0.1196)	-0.082433 (0.3335)	-0.118484 (0.1749)	-0.04344 (0.4294)	-0.140707 (0.2831)	-0.172971 (0.0337)	-0.078714 (0.0874)
Ethereum							
+	-0.03712 (0.5704)	0.049106 (0.5506)	-0.129198 (0.2925)	0.054779 (0.2761)	-0.077705 (0.6539)	-0.103456 (0.2400)	-0.024995 (0.6993)
-	-0.059376 (0.3958)	-0.108322 (0.2161)	-0.168304 (0.1501)	-0.04688 (0.3985)	-0.157055 (0.3089)	-0.225622 (0.0194)	-0.086329 (0.1954)

Table 5 The Long run asymmetry test of Wald

	S&P500	CAC40	DAX30	FTSE	FTSEMIB	NIKKEI	SPTSX
Bitcoin							
Gold							
+	0.499473 (0.2427)	0.397123 (0.5197)	0.954602 (0.1866)	-0.048557 (0.8998)	0.197974 (0.7945)	1.591256 (0.0379)	0.531600 (0.2388)
-	0.748922 (0.1002)	1.153672 (0.0820)	1.665576 (0.039)	0.507858 (0.2362)	0.598245 (0.5048)	1.597309 (0.0429)	1.310587 (0.0106)
WTI							
+	0.358938 (0.0520)	0.358616 (0.1720)	0.328391 (0.2852)	0.319244 (0.0640)	0.442256 (0.1916)	0.045567 (0.8849)	0.364453 (0.0550)
-	0.282198 (0.0043)	0.292654 (0.0306)	0.237031 (0.1251)	0.249809 (0.0050)	0.439809 (0.0359)	0.316604 (0.0387)	0.181797 (0.0645)
Litecoin							
Gold							
+	0.345942 (0.4017)	0.213432 (0.7503)	0.498402 (0.4259)	-0.235853 (0.5407)	0.142715 (0.8801)	1.264855 (0.1128)	0.176125 (0.6270)
-	0.639801 (0.0992)	1.514345 (0.0228)	1.816539 (0.0055)	0.658094 (0.100)	0.993399 (0.3062)	1.294358 (0.0757)	1.192730 (0.0016)
WTI							
+	0.365346 (0.0313)	0.541973 (0.0565)	0.515052 (0.0626)	0.470786 (0.0062)	0.758427 (0.0688)	0.229313 (0.4628)	0.411715 (0.0105)
-	0.187174 (0.0792)	0.210182 (0.2160)	0.120259 (0.4654)	0.203984 (0.0473)	0.366598 (0.1953)	0.154171 (0.4112)	0.012527 (0.8912)
Bitcoin gold							
Gold							
+	0.659113 (0.1908)	0.417244 (0.5444)	0.681881 (0.3445)	-0.117617 (0.7518)	0.516033 (0.6026)	1.274468 (0.1199)	0.384042 (0.3841)
-	0.621185 (0.1379)	1.220764 (0.0543)	1.624538 (0.0230)	0.533772 (0.1367)	0.842952 (0.3578)	1.237156 (0.0946)	1.134907 (0.0086)
WTI							
+	0.301481 (0.1159)	0.481597 (0.0748)	0.508721 (0.0790)	0.412137 (0.0076)	0.572436 (0.1318)	0.149784 (0.6401)	0.396833 (0.0226)
-	0.394508 (0.0228)	0.307928 (0.1665)	0.283987 (0.2559)	0.282108 (0.0269)	0.616988 (0.1100)	0.25187 (0.3201)	0.176879 (0.2428)
Maker							
Gold							
+	0.520337 (0.2356)	0.356987 (0.5193)	0.616828 (0.3927)	-0.154906 (0.6382)	0.280727 (0.7312)	1.453932 (0.1030)	0.403904 (0.3425)
-	0.554453 (0.1237)	1.251272 (0.0108)	1.700247 (0.0124)	0.603303 (0.0411)	1.255557 (0.0937)	1.394160 (0.0606)	1.153682 (0.0033)
WTI							

Table 5 (continued)

	S&P500	CAC40	DAX30	FTSE	FTSEMIB	NIKKEI	SPTSX
+	0.213126 (0.3224)	0.296755 (0.3032)	0.537950 (0.1810)	0.284057 (0.1065)	0.739548 (0.1291)	0.118375 (0.7814)	0.333239 (0.1430)
-	0.263703 (0.0134)	0.21633 (0.0917)	0.172164 (0.3173)	0.181888 (0.0195)	0.456309 (0.0722)	0.268821 (0.1663)	0.129662 (0.1915)
Dash							
Gold							
+	0.36418 (0.3763)	0.018204 (0.9752)	0.369481 (0.5177)	-0.352255 (0.3206)	0.086824 (0.9217)	0.860910 (0.1237)	0.072795 (0.8064)
-	0.815063 (0.0264)	1.475206 (0.0122)	1.859487 (0.0031)	0.701601 (0.0562)	1.441708 (0.1060)	1.59762 (0.0049)	1.186343 (0.0002)
WTI							
+	0.393332 (0.0167)	0.51438 (0.0426)	0.511455 (0.0603)	0.459017 (0.0050)	0.840641 (0.0468)	0.22203 (0.3565)	0.305026 (0.0265)
-	0.275304 (0.0037)	0.182321 (0.1405)	0.17545 (0.1694)	0.171934 (0.0280)	0.486033 (0.0926)	0.22385 (0.0406)	0.099619 (0.1121)
Ethereum							
Gold							
+	0.488555 (0.2465)	0.276419 (0.5834)	0.555721 (0.3783)	-0.185174 (0.5484)	0.228895 (0.7869)	1.112427 (0.0451)	0.364613 (0.3269)
-	0.712019 (0.0730)	1.519397 (0.0025)	1.99733 (0.0037)	0.731298 (0.0186)	1.386256 (0.1117)	1.635983 (0.0032)	1.298955 (0.0009)
WTI							
+	0.372528 (0.0552)	0.41263 (0.0845)	0.673493 (0.0483)	0.355316 (0.0186)	0.816065 (0.0916)	0.230498 (0.3752)	0.389815 (0.0376)
-	0.293378 (0.0024)	0.254586 (0.0210)	0.229952 (0.1042)	0.209261 (0.0030)	0.523028 (0.0545)	0.289302 (0.0125)	0.172207 (0.0354)

Table 6 Estimation results for the S&P500

	X = Bitcoin	X = Litecoin	X = Bitcoin gold	X = Maker	X = Dash	X = Ethereum
ARDL model	(2, 0, 0, 4, 2, 0, 0)	(2, 1, 0, 4, 2, 0, 0)	(2, 0, 0, 4, 2, 0, 0)	(2, 0, 0, 4, 2, 0, 0)	(2, 0, 0, 4, 2, 0, 0)	(2, 0, 0, 4, 2, 0, 0)
CointEq(- 1)	- 0.050868 (0.0000)	- 0.054499 (0.0000)	- 0.047374 (0.0000)	- 0.053310 (0.0000)	- 0.056066 (0.0000)	- 0.050411 (0.0000)
dy(- 1)	- 0.295672 (0.0000)	- 0.295640 (0.0000)	- 0.299265 (0.0000)	- 0.294462 (0.0000)	- 0.293939 (0.0000)	- 0.296350 (0.0000)
dx1p		- 0.03639 (0.0649)				
dx2p	- 0.093766 (0.2910)	- 0.099088 (0.2712)	- 0.097556 (0.2720)	- 0.106263 (0.2324)	- 0.084846 (0.3379)	- 0.089459 (0.3133)
dx2p(- 1)	0.157664 (0.0791)	0.154761 (0.0880)	0.148779 (0.0981)	0.142645 (0.1136)	0.169852 (0.0573)	0.162513 (0.0698)
dx2p(- 2)	- 0.027377 (0.7576)	- 0.014319 (0.8733)	- 0.036593 (0.6804)	- 0.036480 (0.6815)	- 0.016541 (0.8515)	- 0.022737 (0.7974)
dx2p(- 3)	0.208442 (0.0178)	0.206332 (0.0195)	0.199875 (0.0232)	0.199723 (0.0233)	0.218905 (0.0125)	0.212676 (0.0155)
dx2n	0.240056 (0.0214)	0.242917 (0.0209)	0.233978 (0.0246)	0.242781 (0.0200)	0.239133 (0.0216)	0.235672 (0.0237)
dx2n(- 1)	0.252715 (0.0147)	0.272656 (0.0087)	0.256532 (0.0133)	0.265649 (0.0105)	0.245491 (0.0216)	0.250420 (0.0156)
DW stat	1.904064	1.902742	1.904045	1.903506	1.904767	1.904532
AIC	- 5.606225	- 5.608901	- 5.607360	- 5.606762	- 5.609484	- 5.606938
SIC	- 5.544902	- 5.539912	- 5.546037	- 5.545439	- 5.548161	- 5.545615
F-statistic	3.230714***	3.48581**	3.312607**	3.269394***	3.466078**	3.282132**

The probability values given in parentheses ()

*** and ** indicates that the model is globally significant in 5% and 1% level

Table 7 Estimation results for CAC40

	X = Bitcoin	X = Litecoin	X = Bitcogold	X = Maker	X = Dash	X = Ethereum
ARDL model	(2, 2, 1, 2, 0, 0, 0)	(2, 0, 0, 1, 0, 0, 0)	(2, 0, 0, 1, 0, 0, 0)	(2, 2, 0, 1, 0, 0, 0)	(2, 0, 0, 1, 0, 0, 0)	(2, 0, 0, 1, 0, 0, 0)
CointEq(- 1)	- 0.039288 (0.0000)	- 0.036154 (0.0001)	- 0.036058 (0.0000)	- 0.045277 (0.0000)	- 0.041147 (0.0000)	- 0.046357 (0.0000)
dy(- 1)	0.080521 (0.0494)	0.089928 (0.0297)	0.087897 (0.0333)	0.098053 (0.0173)	0.092426 (0.0254)	0.095572 (0.0208)
dx1p	0.009288 (0.7450)			0.018447 (0.4251)		
dx1p(- 1)	0.085545 (0.0031)			- 0.071354 (0.0026)		
dx1n	0.084641 (0.0007)					
dx2p	- 0.202272 (0.0399)	- 0.186538 (0.0458)	- 0.182690 (0.0501)	- 0.164885 (0.0931)	- 0.177829 (0.0563)	- 0.171676 (0.0649)
dx2p(- 1)	0.161977 (0.1069)					
DW stat	1.992408	2.004759	2.004282	2.002909	2.005543	2.007943
AIC	- 5.299106	- 5.275515	- 5.277619	- 5.285933	- 5.277694	- 5.279525
SIC	- 5.245594	- 5.252612	- 5.254717	- 5.247710	- 5.254791	- 5.256622
F-statistic	2.125654***	2.020906***	2.172356***	2.562476**	2.177711***	2.309773**

** and *** indicates that the model is globally significant in 5% and 1% level

Table 8 Estimation results for DAX30

	X = Bitcoin	X = Litecoin	X = Bitcoin gold	X = Maker	X = Dash	X = Ethereum
ARDL model	(1, 2, 1, 1, 1, 0, 0)	(1, 2, 1, 0, 1, 0, 0)	(1, 0, 0, 0, 1, 0, 0)	(1, 2, 1, 0, 1, 0, 0)	(1, 0, 0, 0, 1, 0, 0)	(1, 0, 0, 0, 1, 0, 0)
CointEq(-1)	-0.033206 (0.0004)	-0.037246 (0.0001)	-0.032687 (0.0002)	-0.034035 (0.0001)	-0.040351 (0.0001)	-0.035131 (0.0001)
dy(-1)						
dx1p	-0.004297 (0.8808)	0.024448 (0.2803)		0.007507 (0.7446)		
dx1p(-1)	0.080625 (0.0058)	-0.036783 (0.0893)		-0.075058 (0.0015)		
dx1n	0.099797 (0.0001)	-0.041923 (0.0645)		0.047492 (0.0387)		
dx2p	-0.139390 (0.1552)					
dx2n	-0.144822 (0.2054)	-0.162292 (0.1572)	-0.184293 (0.0835)	-0.171586 (0.1217)	-0.167802 (0.1134)	-0.181628 (0.0871)
DW stat	1.949401	1.906392	1.951164	1.934285	1.940336	1.952588
AIC	-5.301450	-5.275157	-5.276861	-5.287801	-5.279330	-5.280611
SIC	-5.255583	-5.236934	-5.261593	-5.249578	-5.264062	-5.265343
F-statistic	1.591329	1.973491	1.772743	2.060435***	1.950166	2.042382***

The probability values given in parentheses ()

*** indicates that the model is globally significant in 1% level

Table 9 Estimation results for the FTSE

	X = Bitcoin	X = Litecoin	X = Bitcoin gold	X = Maker	X = Dash	X = Ethereum
ARDL model	(1, 2, 1, 2, 0, 0, 0)	(2, 0, 0, 2, 0, 0, 0)	(2, 0, 0, 2, 0, 0, 0)	(2, 2, 0, 2, 0, 0, 0)	(2, 0, 0, 2, 0, 0, 0)	(2, 0, 0, 2, 0, 0, 0)
CointEq(-1)	-0.054235 (0.0000)	-0.054076 (0.0000)	-0.056932 (0.0000)	-0.066528 (0.0000)	-0.057342 (0.0000)	-0.065741 (0.0000)
dy(-1)		0.065192 (0.1158)	0.063551 (0.1240)	0.075310 (0.0690)	0.067724 (0.1023)	0.072283 (0.0813)
dx1p	-0.000151 (0.9953)			0.016183 (0.4321)		
dx1p(-1)	0.079120 (0.0021)			-0.055521 (0.0083)		
dx1n	0.073096 (0.0011)					
dx2p	-0.159752 (0.0688)	-0.141278 (0.0989)	-0.139115 (0.1034)	-0.124830 (0.1583)	-0.133856 (0.1180)	-0.132445 (0.1213)
dx2p(-1)	0.194181 (0.0301)	0.172220 (0.0450)	0.168464 (0.0491)	0.172074 (0.0505)	0.186636 (0.0302)	0.179138 (0.0368)
DW stat	1.875280	1.993968	1.993757	2.005534	1.995866	1.997170
AIC	-5.531030	-5.508145	-5.513014	-5.516369	-5.509724	-5.513295
SIC	-5.485163	-5.477567	-5.482436	-5.470502	-5.479145	-5.482716
F-statistic	2.837797**	2.757819**	3.111116*	3.245970*	2.872137*	3.131507*

The probability values given in parentheses ()

*, ** and *** indicates that the model is globally significant in 10% and 5% level

Table 10 Estimation results for the FTSEMIB

	X = Bitcoin	X = Litecoin	X = Bitcoin gold	X = Maker	X = Dash	X = Ethereum
ARDL model	(2, 2, 0, 1, 0, 0, 1)	(2, 0, 0, 1, 0, 0, 1)	(2, 0, 0, 1, 0, 0, 1)	(2, 4, 0, 0, 1, 0, 1)	(2, 0, 0, 0, 1, 0, 1)	(2, 0, 0, 0, 1, 0, 1)
CointEq(- 1)	- 0.023368 (0.0000)	- 0.019499 (0.0000)	- 0.019596 (0.0000)	- 0.023365 (0.0000)	- 0.021245 (0.0000)	- 0.020880 (0.0000)
dy(- 1)	0.085824 (0.0372)	0.088709 (0.0318)	0.088556 (0.0320)	0.102084 (0.0145)	0.093398 (0.0244)	0.093751 (0.0238)
dx1p	0.029702 (0.1755)			0.003097 (0.8666)		
dx1p(- 1)	0.052304 (0.0192)			- 0.041345 (0.0277)		
dx1p(- 2)				0.006330 (0.7383)		
dx1p(- 3)				- 0.045459 (0.0140)		
dx2p	- 0.145066 (0.0613)	- 0.138317 (0.0621)	- 0.139332 (0.0601)			
dx2n				- 0.116901 (0.1782)	- 0.129299 (0.1231)	- 0.132924 (0.1133)
dx3n	- 0.041111 (0.0924)	- 0.041472 (0.0851)	- 0.036420 (0.1305)	- 0.035075 (0.1494)	- 0.039540 (0.0987)	- 0.039751 (0.0970)
R-squared	0.060579	0.048926	0.049899	0.065014	0.049756	0.049575
DW stat	1.986061	2.008664	2.008759	1.997304	2.005016	2.005606
AIC	- 5.780606	- 5.776752	- 5.777775	- 5.785118	- 5.777625	- 5.777435
SIC	- 5.734551	- 5.746091	- 5.747114	- 5.723543	- 5.746964	- 5.746774
F-statistic	2.291559**	2.266950**	2.340280**	2.729599**	2.543864**	2.530168**

The probability values given in parentheses ()

** indicates that the model is globally significant in 5% level

Table 11 Estimation results for NIKKEI

	X = Bitcoin	X = Litecoin	X = Bitcoin gold	X = Maker	X = Dash	X = Ethereum
ARDL model	(1, 0, 1, 0, 0, 0)	(1, 2, 1, 0, 0, 0)	(1, 0, 0, 0, 0, 0)	(1, 0, 1, 0, 0, 0)	(1, 0, 0, 0, 0, 0)	(1, 0, 0, 0, 0, 0)
CointEq(-1)	-0.037163 (0.0000)	-0.036681 (0.0002)	-0.034473 (0.0003)	-0.034018 (0.0001)	-0.047591 (0.0000)	-0.046764 (0.0000)
dxIp		0.011326 (0.6399)				
dxIp(-1)		-0.061243 (0.0106)				
Dx ln	0.119061 (0.0000)	-0.046971 (0.0494)		0.068636 (0.0054)		
DW stat	2.090808	2.063869	2.078325	2.058585	2.064330	2.070828
AIC	-5.092115	-5.065998	-5.065013	-5.070548	-5.071226	-5.072934
SIC	-5.076846	-5.035419	-5.057389	-5.055280	-5.063602	-5.065310
F-statistic	2.269556**	1.778602	1.617040	1.891418	2.064979***	2.188607***

The probability values given in parentheses ()

** and *** indicates that the model is globally significant in 5% and 1% level

Table 12 Estimation results for the SPTSX

	X = Bitcoin	X = Litecoin	X = Bitcoin gold	X = Maker	X = Dash	X = Ethereum
ARDL model	(1, 0, 1, 0, 0, 0)	(1, 2, 0, 0, 0, 0)	(1, 0, 0, 0, 0, 0)	(1, 2, 1, 0, 0, 0)	(1, 0, 0, 0, 0, 0)	(1, 0, 0, 0, 0, 0)
CointEq(-1)	-0.038818 (0.0000)	-0.046766 (0.0000)	-0.039793 (0.0000)	-0.042626 (0.0000)	-0.055568 (0.0000)	-0.044503 (0.0000)
dy(-1)				0.012718 (0.4536)		
dx1p		-0.004933 (0.7580)		-0.066334 (0.0001)		
dx1p(-1)		-0.040120 (0.0087)				
dx1n	0.057877 (0.0010)			0.043715 (0.0098)		
DW stat	2.053475	2.003641	2.021093	2.006301	2.002027	2.014988
AIC	-5.904564	-5.897794	-5.893140	-5.914533	-5.900599	-5.895588
SIC	-5.889296	-5.874860	-5.885516	-5.883954	-5.892975	-5.887964
F-statistic	2.394571**	2.910353*	2.320500**	3.109829*	2.863791**	2.498378**

The probability values given in parentheses ()

* and ** indicates that the model is globally significant in 10% and 5% level

According to the AIC and SIC information criteria,⁵ we have obtained the NARDL specification model.

The error correction term is negatively significant in all the estimated models and no autocorrelation problem is confirmed by the DW statistic.

Therefore, the above findings suggest that the stock prices asymmetrically respond to the crypto-currency movements in both the short and long run. Hence, this result is aligned with that of Bouri, Gupta et al. (2018) who found asymmetric and nonlinear correlations between Bitcoin and the aggregate commodity index, and between Bitcoin and gold prices.

4.1 The long-term relationship (Tables 4 and 5)

Regarding the results shown in Table 4, the positive coefficient of Bitcoin is more important than the negative coefficient for all stock prices, except for the S&P500. This means that in the long run, stock prices, in general, respond only to rising Bitcoin. This finding would improve the sensibility of stock prices to increases more than to decreases. Moreover, the asymmetric effect of Bitcoin is higher on CAC40 (0.102) in comparison to other values.

On the other hand, Litecoin has an important positive asymmetric effect on CAC40, DAX30, and FTSE, but for the other stock prices, the values of the negative asymmetric effect are higher. These results mean that the first group of stock prices respond more to the rising movements of Litecoin than to the decreasing ones. However, the second group of stock prices is more sensitive to the decreasing movements of Litecoin.

Concerning the asymmetric effect of Bitcoin gold, we found that the negative effect of the crypto-currency is higher than the positive one. This result means that all stock prices respond more to the decreasing movements of Bitcoin gold in the long run. Contrarily to the Bitcoin gold effect, the asymmetric effect of Maker on all stock prices shows that the positive effect is more important than the negative one, except for DAX30. This result implies that, in the long run, the stock prices are more sensitive to the increasing than to the decreasing movements of Maker.

Moreover, the values of the positive and negative asymmetric effects of Dash and Ethereum are mixed. In the long run, the stock prices sometimes respond more to the increasing movements of the two crypto-currencies while the other stock prices respond more to the decreasing ones. Therefore, we can conclude that the rising movements have a greater influence on the stock prices than the declining ones, meaning that crypto-currency movements can change the behavior of the stock prices. In fact, according to Baur and Lucey (2010), the evidence on the positive relationship between crypto-currencies and stock prices suggests a weak safe haven role for crypto-currencies in the long run. Therefore, this finding is in line with those of Bouoiyour and Selmi (2015) but contradicts that of some prior studies that used different models, such as that of Bouri, Jalkh et al. (2017) and Bouri, Molnár et al. (2017).

According to the results shown in Table 5, the values of the negative movements of gold are higher than the positive ones on all stock prices accounting

⁵ The best model is the one that has the lowest AIC and SIC values.

for all crypto-currencies, except for the Bitcoin gold on NIKKEI and Maker on NIKKEI. This result means that the stock prices, in general, respond to the decreasing movements of gold more than to the increasing ones. Therefore, the negative relationship between stock and gold prices seems contradictory to the weak safe haven evidence shown above.

This means that gold can act as a good hedging instrument or a safe haven against stock prices. This could be partially explained by the fact that gold is still assumed to be uncorrelated with other assets, which is an important characteristic in an age of globalization in which correlations among most asset types grew dramatically.

This result is therefore aligned with that of Baur and Lucey (2010), who suggested that gold acts as a safe-haven in extreme stock market conditions. In fact, Baur and McDermott (2010) confirmed the safe-haven property of gold for the US and big stock markets in Europe, and more recently Ji et al. (2020), who indicated that gold has remained robust (strong) as a safe-haven asset during the COVID-19 pandemic. However, this result contradicts that of Jeribi and Snene-Manzli (2021), who indicated that gold was neither hedge nor a safe haven for the Tunisian investors during the COVID-19 outbreak. It also contradicts the results of Shahzad et al. (2019) who found that gold is a weak safe haven and Cheema et al. (2020) who found that gold fails to protect the investors' wealth during the COVID-19 pandemic.

Inversely, the values of the positive movements of WTI are more important than the negative ones on all the stock prices accounting for all crypto-currencies, except for the Bitcoin gold on FTSEMIB and on NIKKEI, Maker on NIKKEI, Dash on NIKKEI, and Ethereum on NIKKEI. This result means that the stock prices, in general, respond to the increasing movements of WTI more than the decreasing ones. Like in the case of crypto-currencies, this finding suggests a weak safe haven role for the Oil index in the long run, which implies that this result is in line with that of Ciner et al. (2013), who suggested that, in general, oil does not act as a safe haven asset for the stock markets. Moreover, the positive asymmetric relationship captured between crypto-currencies/WTI and the stock market indices suggests a diversifier role of these assets against the stock prices.

Therefore, based on the values shown in Tables 4 and 5, we can affirm that among all the stock market prices, FTSEMIB is more sensitive to the different crypto-currencies, gold, and WTI. This can be explained by the higher effect of the COVID-19 pandemic in Italy more than in the other countries.

4.2 The short-run effect (Tables 6, 7, 8, 9, 10, 11 and 12)

Table 6 shows the results of the short-term relationship between the S&P500 and the chosen crypto-currencies. All the error correction terms are negatively significant. The coefficient of the co-integration equation is defined as the speed adjustment where the dependent variable returns converge towards the equilibrium level. On the other hand, the error correction term connects the deviation of the last period relative to the long-term equilibrium, which can influence the short-term dynamics of

the dependent variable. Therefore, the variation of the S&P500 in the last period is negatively significant in general. However, in the short run, only Litecoin can have a positive asymmetric influence on the S&P500, and this stock price responds to the negative movements of gold for all the crypto-currencies.

Table 7 shows the results of the short-term relationship between CAC40 and the chosen crypto-currencies where all the error correction terms are negatively significant. In the short run, only Bitcoin and Maker can have a positive asymmetric influence on the CAC40, and this stock price responds to the positive movements of gold for all the crypto-currencies. Then, Table 8 shows the results of the short-term relationship between DAX30 and the chosen crypto-currencies where all the error correction terms are also negatively significant. Moreover, in the short run, Bitcoin and Litecoin have a positive asymmetric effect on DAX30 more important than the decreasing movement, however, Maker negatively and asymmetrically influences DAX30, and this stock price responds to the negative movements of gold for all the crypto-currencies.

Table 9 shows the results of the short-term relationship between FTSE and the chosen crypto-currencies where all the error correction terms are negatively significant. In the short run, only Bitcoin and Maker have a positive asymmetric effect on FTSE more important than the decreasing movement, and this stock price responds to the positive movements of gold for all the crypto-currencies.

As for Table 10, it shows the results of the short-term relationship between FTSEMIB and the chosen crypto-currencies where all the error correction terms are also negatively significant. In the short run, only the Bitcoin and Maker have a positive asymmetric effect on FTSEMIB, and the latter responds to the positive movements of gold for Bitcoin, Litecoin, and Bitcoin gold models and responds to the negative movements of gold for the other crypto-currencies models. On the other hand, Table 11 shows the results of the short-term relationship between NIKKEI and the chosen crypto-currencies where all the error correction terms are negatively significant. In the short run, only Litecoin has a positive asymmetric effect on NIKKEI, and the latter responds only to the negative movements of Bitcoin and Maker.

Finally, Table 12 shows the results of the short-term relationship between SPTSX and the chosen crypto-currencies where all the error correction terms are also negatively significant. In the short run, only Litecoin has a positive asymmetric effect on SPTSX, and the latter responds to the negative movements of Bitcoin and Maker.

Therefore, based on the results shown in Tables 6, 7, 8, 9, 10, 11 and 12, we can conclude that crypto-currencies can influence the seven stock prices in the long run more importantly than in the short run. In addition, we have concluded that in the short run, only Bitcoin, Litecoin, and Maker have an asymmetric effect on the chosen stock prices. In most cases, these three digital assets have an asymmetric positive effect on the chosen stock prices. This result indicates that Bitcoin, Litecoin, and Maker do not act as good hedging and safe-haven assets for stock markets. Therefore, this result seems to be aligned with those of Brière et al. (2015), Bourri, Jalkh et al. (2017), Kajtazi and Moro (2018), Guesmi et al. (2019), Charfeddine et al. (2020), among others, who suggested a significant portfolio diversification and risk management gains when a crypto-currency, especially Bitcoin, is incorporated.

Moreover, these findings demonstrate that positive and negative returns of gold significantly affect the stock markets in the short run. Therefore, the null hypothesis of short-term symmetry is rejected for most cases, suggesting that short-term positive and negative returns of gold have asymmetrical effects on the stock markets.

Moreover, the negative asymmetric short effect of gold dominates the positive one, improving the hedging and safe-haven role of gold. As a consequence, this finding supports the results in the long run presented above.

4.3 Multiplier impact

The graphs of the multiplier impact trace the dynamic response of stock prices following the negative and positive shocks of crypto-currencies.

By analyzing Fig. 1 of the multiplier impact of Bitcoin on the stock market prices, we can see that the effect of positive shocks on all the stock prices, except for the S&P500, dominates that of negative ones. However, in the long run, the asymmetric response of the different stock prices to Bitcoin shocks is far from zero, which confirms the results of the estimated coefficients.

By analyzing Fig. 2 of the multiplier impact of Litecoin on the stock market prices, we see that the effect of positive shocks dominates that of negative only in the case of CAC40, DAX30, and FTSE. However, in the other stock prices, the effect of negative shocks dominates. We can conclude that the stock indexes are more sensitive to a decline in the value of Litecoin than to an increase. Nevertheless, CAC40, DAX30, and FTSE are more sensitive to the increasing movements of Litecoin. The asymmetric response of the different stock prices to Litecoin shocks is far from zero in the long run, which confirms the results of the estimated coefficients.

By analyzing Fig. 3 of the multiplier impact of Bitcoin gold on the stock market prices, we see that the effect of negative shocks dominates that of positive ones in all stock indexes except for the S&P500. We can conclude that the stock prices are more sensitive to a decrease in the price of Bitcoin gold than to an increase. Nevertheless, the S&P500 is more sensitive to the increasing movements of Bitcoin gold. This result is opposite to the asymmetric response of all the stock indexes to Bitcoin, which confirms the results of the estimated coefficients.

On the other hand, by analyzing Fig. 4 of the multiplier impact of Maker on the stock markets, we see that the effect of positive shocks dominates that of negative ones in all stock prices, except for the S&P500 and DAX30. The asymmetric response of the different stock markets to Maker shocks is far from zero in the long run. We can conclude that the stock markets are more sensitive to an increase in the price of Maker than to a decline. Nevertheless, the S&P500 and DAX30 are more sensitive to the decreasing movements of Maker. This result is very similar to Bitcoin shocks on all the stock indexes.

By analyzing Fig. 5 of the multiplier impact of Dash on the stock market prices, we show that the effect of negative shocks dominates that of positive ones in the case of the S&P500, DAX30, FTSE, and FTSEMIB. However, in the other stock markets, the effect of positive shocks dominates. The asymmetric response of the different stock markets to Dash shocks is far from zero in the long-term

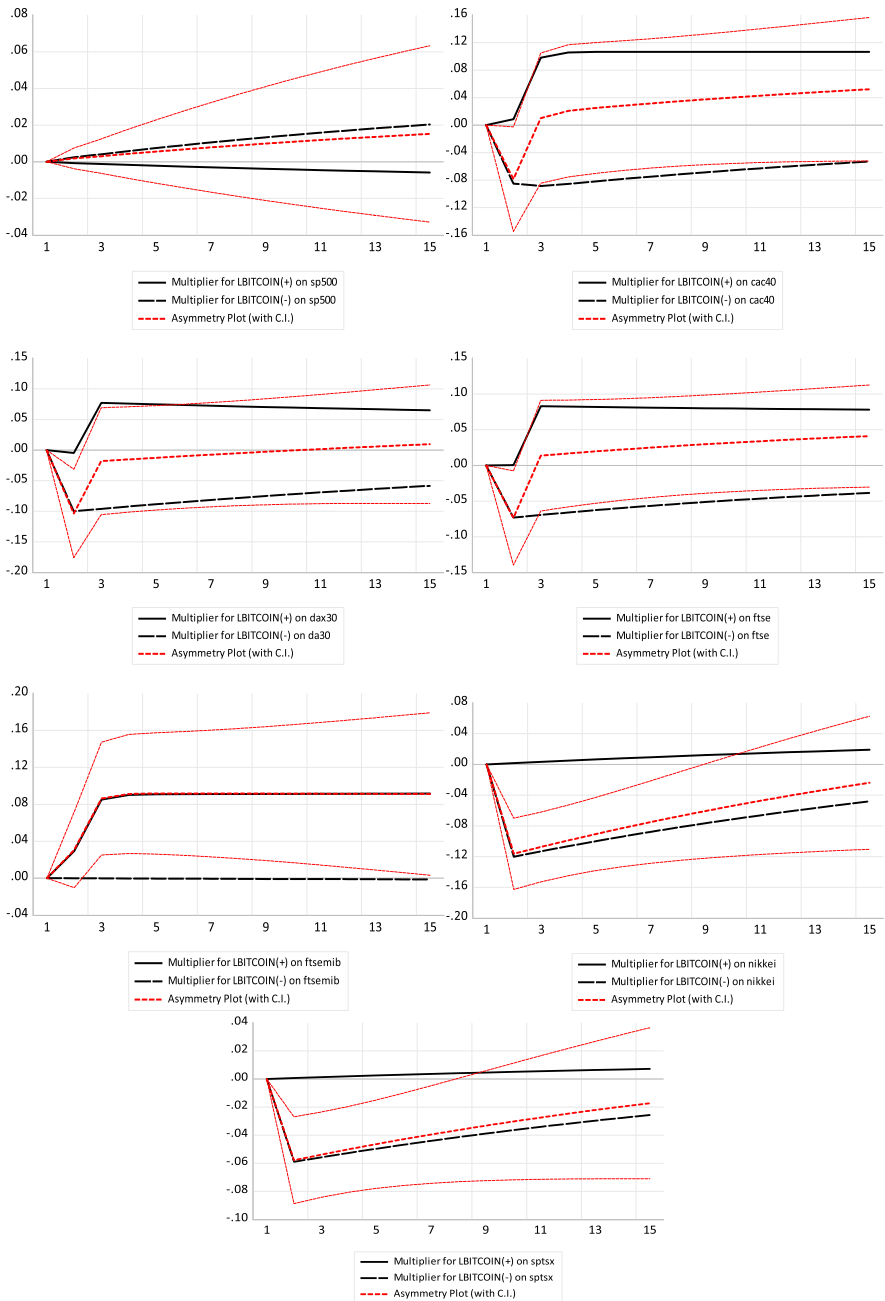


Fig. 1 Multiplier impact of Bitcoin on stock prices

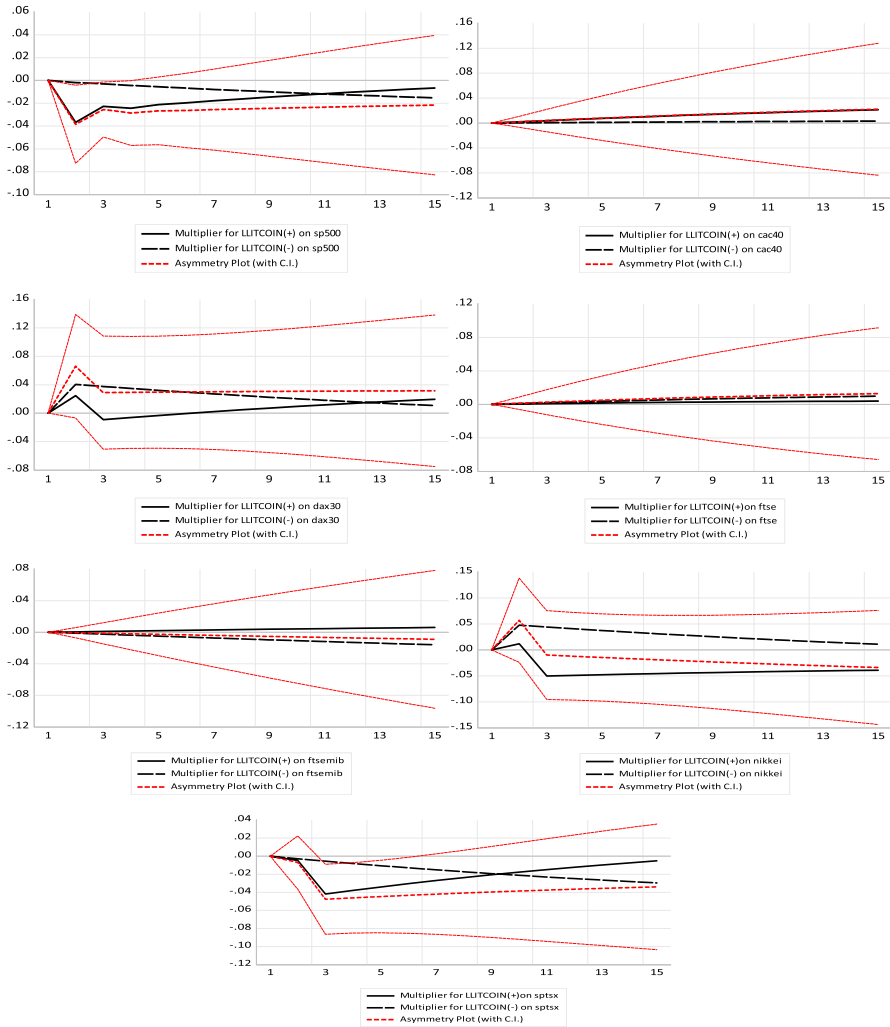


Fig. 2 Multiplier impact of Litecoin on stock prices

relationship, which confirms the results of the estimated coefficients. Figure 5 proves that the stock prices are more sensitive to a decrease in the value of Dash than to an increase. Nevertheless, the S&P500, DAX30, FTSE, and FTSEMIB are more sensitive to the increasing movements of Dash.

Figure 6 of the multiplier impact of Ethereum on the stock indexes indicates that the effect of negative shocks dominates that of positive ones in all stock markets, except for CAC40 and FTSE. The asymmetric response of the different stock prices to Ethereum shocks is far from zero in the long run, which confirms the results of the estimated coefficients. Figure 6 confirms that the stock indexes are more sensitive to a decrease in the value of Ethereum than to an increase. Nevertheless, CAC40 and FTSE are more sensitive to the increasing movements of Ethereum.

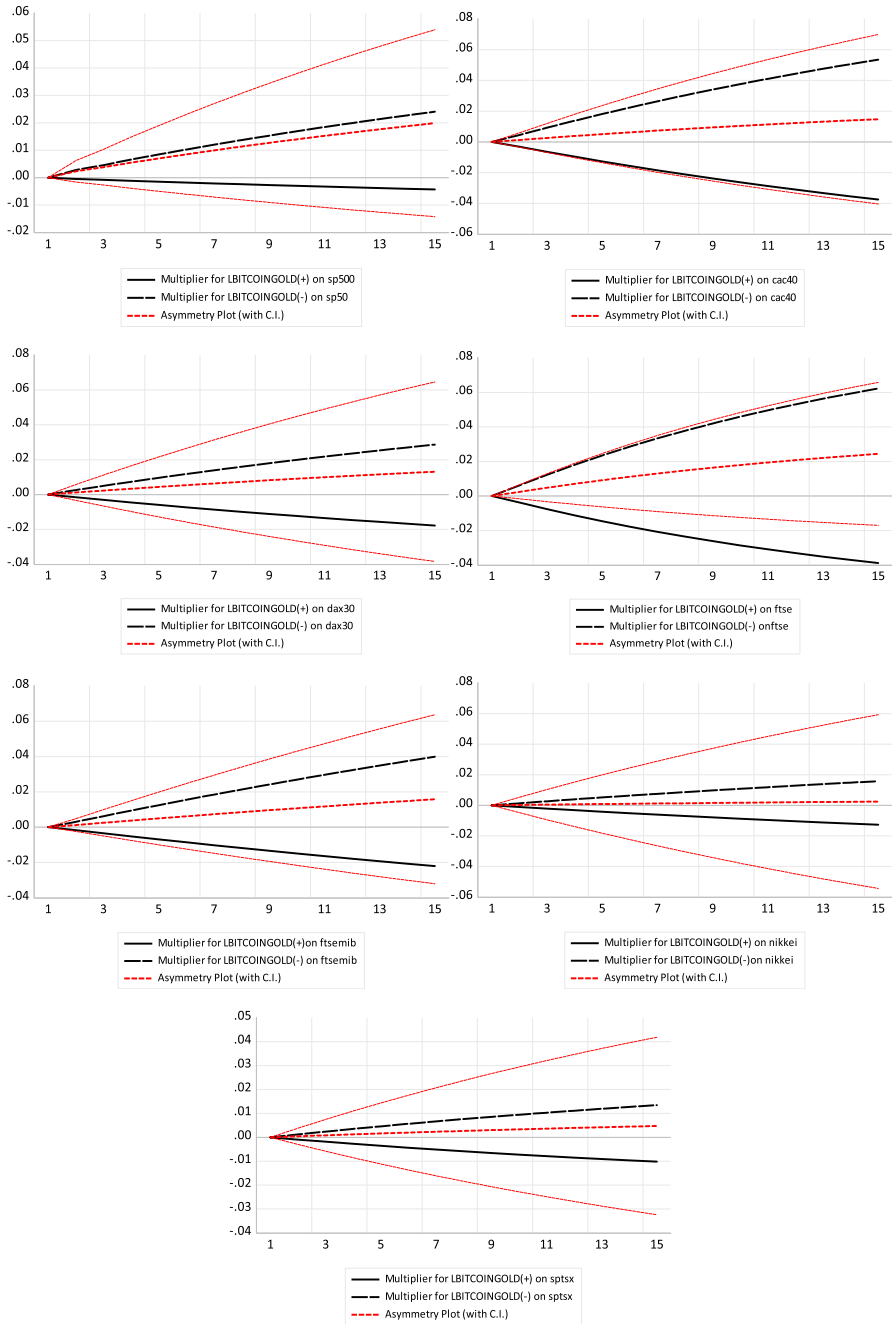


Fig. 3 Multiplier impact of Bitcoin gold on stock prices

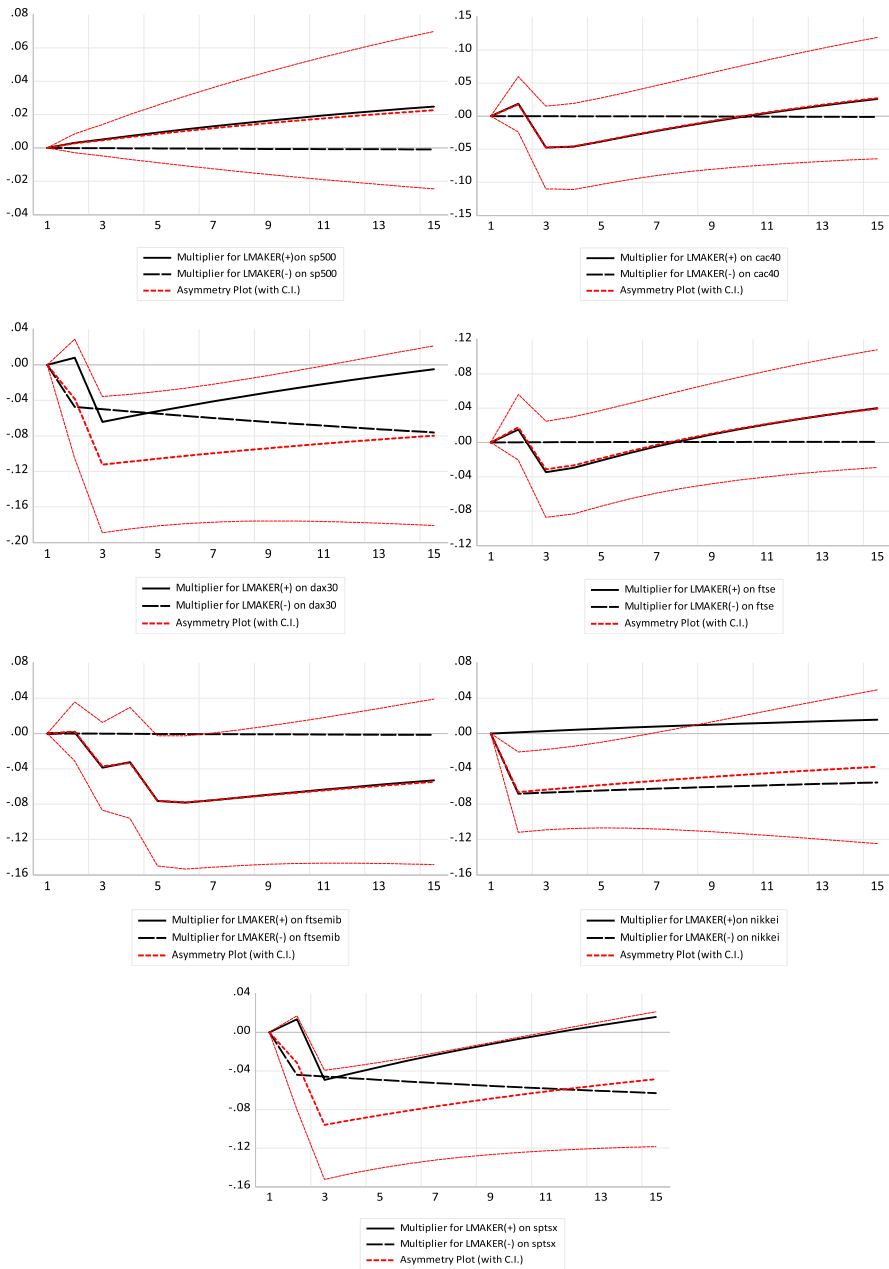


Fig. 4 Multiplier impact of Maker on stock prices

According to these graphs, we can observe that there is a significant shock transmission between crypto-currencies and the different stock markets. Therefore, we can conclude that the majority of the stock prices respond more to the negative

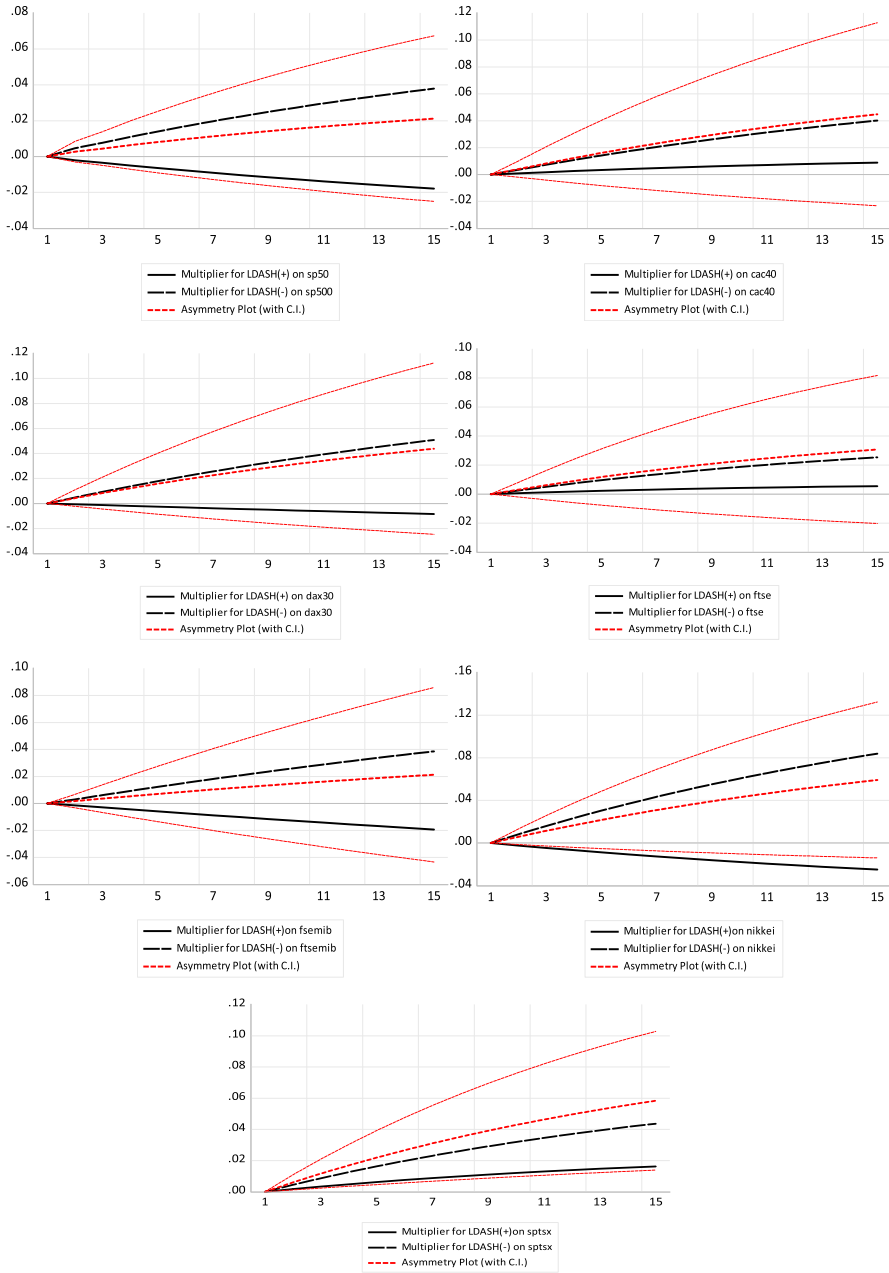


Fig. 5 Multiplier impact of Dash on stock prices

shocks of crypto-currencies than to the positive ones. Therefore, this result looks aligned with those of Baur and Dimpfl (2018), Umar et al. (2020), Sami and Abdallah (2020), Kurka (2019), and Fakhfekh and Jeribi (2019), among others.

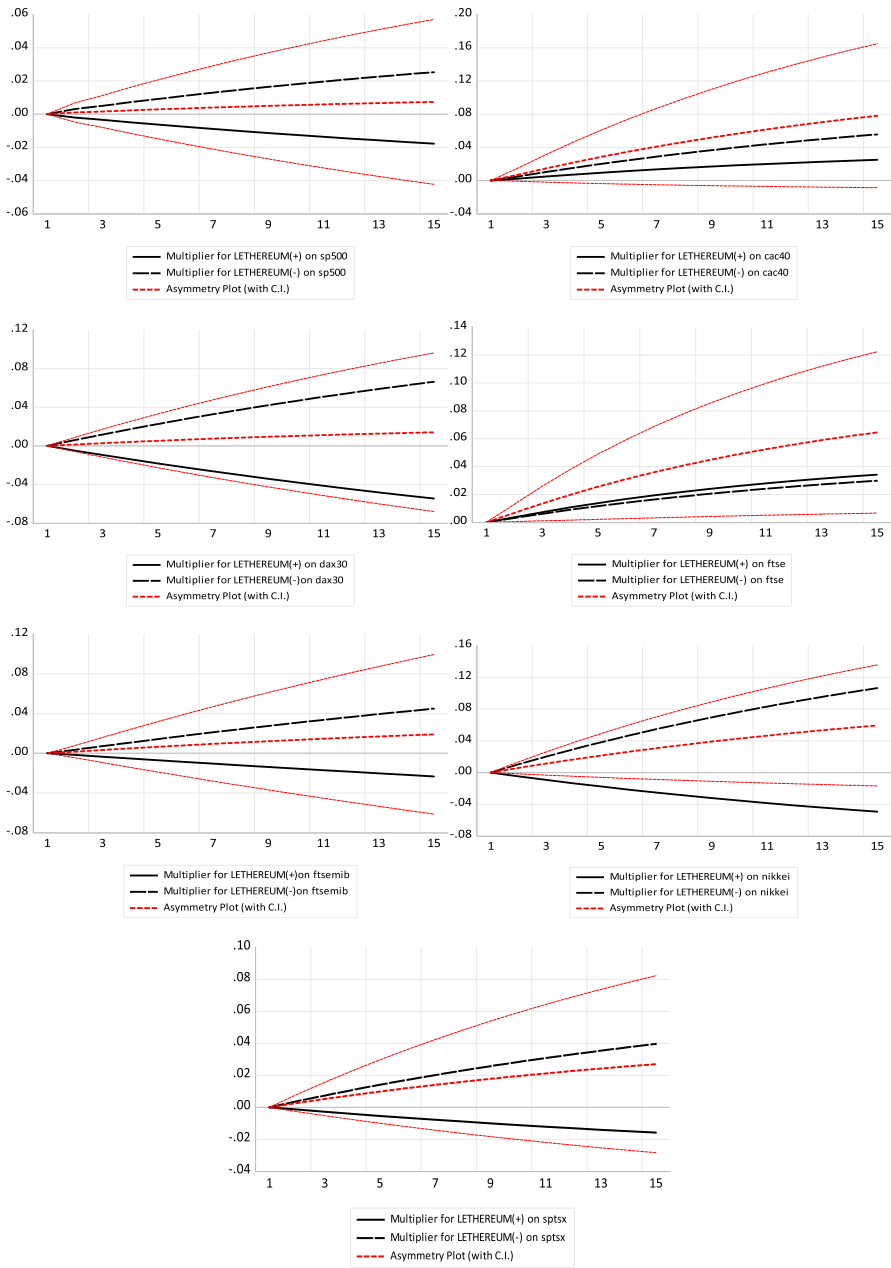


Fig. 6 Multiplier impact of Ethereum on stock prices

5 Conclusion

Practitioners and scholars have recently begun to investigate the relationship between crypto-currencies and stock markets. However, little has been written about the asymmetric effect of crypto-currencies on the G7 stock indexes. Using the NARDL model for the period ranging from 01 January 2019 to 23 February 2021 (including the COVID-19 pandemic period), we uncovered asymmetric correlations between the stock indexes and digital assets in both the short and long run.

In the long run, our results revealed that the rising movements of crypto-currencies have an influence on the stock prices greater than the declining ones. Therefore, this positive asymmetric relationship between the digital and financial assets suggests a weak safe haven role for crypto-currencies in the long run. As for gold, the results indicated that the stock prices, in general, respond to the decreasing movements of gold more than the increasing ones. Therefore, this negative asymmetric relationship between the stock indexes and gold prices leads to the conclusion that gold can act as a good hedging instrument or a safe haven against the stock markets. Moreover, our results suggested a weak safe haven role for the oil index in the long run. Whereas, in the short run, the results revealed that only Bitcoin, Litecoin, and Maker have an asymmetric effect on the selected stock prices with a positive effect in most cases. In fact, this result makes us conclude that these digital assets do not act as good hedging and safe-haven instruments for the stock markets. Inversely for gold, the negative asymmetric short-term effect of gold dominates the positive one, improving the hedging and safe-haven role of the yellow metal. Therefore, these findings support the results of the long run presented above.

On the other hand, while examining the dynamic response of the stock indexes to the negative and positive shocks of crypto-currencies, we concluded that the majority of the stock prices respond to the negative shocks of crypto-currencies more than to the positive ones.

Finally, our study indicated that crypto-currencies and commodities (gold and WTI) are significant driving factors for the stock markets. Therefore, these results are consistent with the literature stating that safe-haven assets can change over time and across countries, for this reason, they can be useful for investors when they decide to implement diversification strategies.

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Declarations

Conflict of interest The corresponding author states that there is no conflict of interest.

References

- Al-Awadhi, A. M., Al-Saifi, K., Al-Awadhi, A., & Alhamadi, S. (2020). Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance*, 27, 100326.
- Anagnostidis, P., Varsakelis, C., & Emmanouilides, C. J. (2016). Has the 2008 financial crisis affected stock market efficiency? The case of Eurozone. *Physica A: Statistical Mechanics and Its Applications*, 447, 116–128.
- Aslanidis, N., Bariviera, A.-F., & Martínez-Ibañez, O. (2019). An analysis of cryptocurrencies conditional cross correlations. *Finance Research Letters*, 31, 130–137.
- Bader, N. A. (2020). Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance*, 54, 101249.
- Baek, C., & Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters*, 22(1), 30–34.
- Baig, A. S., Butt, H. A., Haroon, O., & Rizvi, S. A. R. (2020). Deaths, panic, lockdowns and US equity markets: The case of COVID-19 pandemic. *Finance Research Letters*, 25, 101701.
- Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, 64, 74–81.
- Banerjee, A., Dolado, J., & Mestre, R. (1998). Error-correction mechanism tests for cointegration in a single-equation framework. *Journal of Time Series Analysis*, 19, 267–283.
- Barndorff-Nielsen, O., Kinnebrock, S., & Shephard, N. (2010). *Measuring downside risk-realized semi-variance. Volatility and time series econometrics: Essays in honor of Robert F. Engle*. Oxford University Press.
- Barunik, J., Kočenda, E., & Vacha, L. (2015). Volatility spillovers across petroleum markets. *The Energy Journal*, 77, 309–329.
- Barunik, J., Kočenda, E., & Vacha, L. (2016). Asymmetric connectedness on the U.S. stock market: Bad and good volatility spillovers. *Journal of Financial Markets*, 27, 55–78.
- Barunik, J., Kočenda, E., & Vacha, L. (2017). Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance*, 77, 39–56.
- Baumöhl, E. (2019). Are cryptocurrencies connected to forex? A quantile cross-spectral approach. *Finance Research Letters*, 29, 363–372.
- Baur, D. G., & Dimpfl, T. (2018). Asymmetric volatility in cryptocurrencies. *Economic Letters*, 173, 148–151.
- Baur, D., Hong, K. H. J., & Lee, A. (2015). Bitcoin-currency or asset? *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2561183>
- Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *The Financial Review*, 45(2), 217–229.
- Baur, D. G., & McDermott, T. K. (2010). Is gold a safe-haven? International evidence. *Journal of Banking & Finance*, 34, 1886–1898.
- BenMim, I., & BenSaïda, A. (2019). Financial contagion across major stock markets: A study during crisis episodes. *The North American Journal of Economics and Finance*, 48, 187–201.
- Black, F. (1976). Studies of stock market volatility changes. In *1976 Proceedings of the American statistical association business and economic statistics section*.
- Blau, B. M. (2017). Price dynamics and speculative trading in bitcoin. *Research in International Business and Finance*, 41, 493–499.
- Bouoiyour, J., & Selmi, R. (2015). What does bitcoin look like? *Annals of Economics and Finance*, 16(2), 449–492.
- Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics*, 50(55), 5935–5949.
- Bouri, E., Gupta, R., Lahiani, A., & Shahbaz, M. (2018). Testing for asymmetric nonlinear short- and long-run relationships between bitcoin, aggregate commodity and gold prices. *Resources Policy*, 57, 224–235. <https://doi.org/10.1016/j.resourpol.2018.03.008>
- Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, 23, 87–95. <https://doi.org/10.1016/j.frl.2017.02.009>

- Bouri, E., Jalkh, N., Molnar, P., & Roubaud, D. (2017). Bitcoin for energy commodities before and after the December 2013 crash: Diversifier, hedge or safe haven? *Applied Economics*, 49(50), 5063–5073.
- Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, 20, 192–198. <https://doi.org/10.1016/j.frl.2016.09.025>
- Bouri, E., Saeed, T., Vinh Vo, X., & Roubaud, D. (2021). Quantile connectedness in the cryptocurrency market. *Journal of International Finance Markets, Institutions and Money*, 71, 101302.
- Brière, M., Oosterlinck, K., & Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management*, 16(6), 365–373.
- Charfeddine, L., Benlagha, N., & Maouchi, Y. (2020). Investigating the dynamic relationship between cryptocurrencies and conventional assets: Implications for financial investors. *Economic Modelling*, 85, 198–217.
- Cheah, E. T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economic Letters*, 130, 32–36.
- Cheema, M. A., Faff, R. W., & Szulczuk, K. (2020). The 2008 global financial crisis and COVID-19 pandemic: How safe are the safe haven assets? *Covid Economics, Vetted and Real-Time Papers*, 34, 88–115.
- Cheung, A., Roca, E., & Su, J. J. (2015). Crypto-currency bubbles: An application of the Phillips–Shi–Yu (2013) methodology on Mt. Gox bitcoin prices. *Applied Economics*, 47(23), 2348–2358.
- Chkili, W. (2021). Modeling Bitcoin price volatility: Long memory vs Markov switching. *Eurasian Economic Review*, 11(3), 433–448. <https://doi.org/10.1007/s40822-021-00180-7>
- Chowdhury, B., Dungey, M., Kangogo, M., Abu Sayeed, M., & Volkov, V. (2019). The changing network of financial market linkages: The Asian experience. *International Review of Financial Analysis*, 64, 71–92.
- Christie, A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics*, 10(4), 407–432.
- Chuen, D. L. K., Guo, L., & Wang, Y. (2017). Cryptocurrency: A new investment opportunity? *The Journal of Alternative Investments*, 20(3), 16–40.
- Ciaian, P., Rajcaniova, M., & Kancs, A. (2016). The economics of Bitcoin price formation. *Applied Economics*, 48(19), 1799–1815.
- Ciner, C., Gurdgiev, C., & Lucey, B. M. (2013). Hedges and safe havens: An examination of stocks, bonds, gold, oil, and exchange rates. *International Review of Financial Analysis*, 29, 202–211.
- Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018a). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, 28–34. <https://doi.org/10.1016/j.econlet.2018.01.004>.
- Corbet, S., Larkin, C., Lucey, B., Meegan, A., & Yarovaya, L. (2018b). The volatility generating effects of macroeconomic news on cryptocurrency returns. pp. 1–30. Available at: https://ssrn.com/abstract_id=3141986
- Dastgir, S., Demir, E., Downing, G., Gozgor, G., & Lau, C. K. M. (2019). The causal relationship between Bitcoin attention and Bitcoin returns: Evidence from the Copula-based Granger causality test. *Finance Research Letters*, 28, 160–164.
- Demir, E., Bilgin, M. H., Karabulut, G., & Doker, A. C. (2020). The relationship between cryptocurrencies and COVID-19 pandemic. *Eurasian Economic Review*, 10(3), 349–360.
- Demir, E., Gozgor, G., Lau, C. K. M., & Vigne, S. A. (2018). Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. *Finance Research Letters*, 26, 145–149.
- Diebold, F., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534), 158–171.
- Diebold, F., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66.
- Dimitriou, D., Kenourgios, D., & Simos, T. (2013). Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH-DCC approach. *International Review of Financial Analysis*, 30, 46–56.
- Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters*, 16, 139–144.
- Fakhfekh, M., & Jeribi, A. (2019). Volatility dynamics of crypto-currencies' returns: Evidence from asymmetric and long memory GARCH models. *Research in International Business and Finance*, 51, 101075. <https://doi.org/10.1016/j.ribaf.2019.101075>.

- Fakhfekh, M., Jeribi, A., Ghorbel, A., & Hachicha, N. (2021). Hedging stock market prices with WTI, gold, VIX and cryptocurrencies: A comparison between DCC, ADCC and GO-GARCH models. *International Journal of Emerging Markets*. <https://doi.org/10.1108/IJOEM-03-2020-0264>.
- Forbes, K., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *The Journal of Finance*, 57(5), 2223–2261.
- French, K., Schwert, G., & Stambaugh, R. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, 19(1), 3–29.
- Gande, A., & Parsley, D. (2005). News spillovers in the sovereign debt market. *Journal of Financial Economics*, 75(3), 691–734.
- Gao, H.-L., & Mei, D.-C. (2019). The correlation structure in the international stock markets during global financial crisis. *Physica A: Statistical Mechanics and Its Applications*, 534, 122056.
- Ghorbel, A., & Jeribi, A. (2021). Investigating the relationship between volatilities of cryptocurrencies and other financial assets. *Decisions in Economics and Finance*, 44(2), 817–843.
- Gil-Alana, L., Abakah, E., & Rojo, M. (2020). Cryptocurrencies and stock market indices. Are they related? *Research in International Business and Finance*, 51, 101063.
- Gozgor, G., Tiwari, A. K., Demir, E., & Akron, S. (2019). The relationship between Bitcoin returns and trade policy uncertainty. *Finance Research Letters*, 29, 75–82.
- Grout, P. A., & Zalewska, A. (2016). Stock market risk in the financial crisis. *International Review of Financial Analysis*, 46, 326–345.
- Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis*, 63, 431–437.
- Hasan, R., & Mohammad, S. M. (2015). Multifractal analysis of Asian markets during 2007–2008 financial crisis. *Physica A: Statistical Mechanics and Its Applications*, 419, 746–761.
- Horta, P., Lagoa, S., & Martins, L. (2014). The impact of the 2008 and 2010 financial crises on the Hurst exponents of international stock markets: Implications for efficiency and contagion. *International Review of Financial Analysis*, 35, 140–153.
- Huang, Y., Duan, K., & Mishra, T. (2021). Is Bitcoin really more than a diversifier? A pre-and post-COVID-19 analysis. *Finance Research Letters*, 43, 102016.
- Jeribi, A., Chamsa, D., & Snene-Manzli, Y. (2020). Emerging stock markets' reaction to COVID-19: Can cryptocurrencies be a safe haven? *Journal of Management and Economic Studies*, 2(3), 152–165.
- Jeribi, A., & Fakhfekh, M. (2021). Portfolio management and dependence structure between cryptocurrencies and traditional assets: Evidence from FIEGARCH-EVT-Copula. *Journal of Asset Management*, 22, 224–239. <https://doi.org/10.1057/s41260-021-00211-7>
- Jeribi, A., Jena, S. K., & Lahiani, A. (2021). Are cryptocurrencies a backstop for the stock market in a COVID-19-led financial crisis? Evidence from the NARDL approach. *International Journal of Financial Studies*, 9(3), 33.
- Jeribi, A., & Masmoudi, W. K. (2021). Investigating dynamic interdependencies between traditional and digital assets during the COVID-19 outbreak: Implications for G7 and Chinese financial investors. *Journal of Research in Emerging Markets*, 3(3), 60–80.
- Jeribi, A., & Snene-Manzli, Y. (2021). Can cryptocurrencies be a safe haven during the novel COVID-19 pandemic? Evidence from the Tunisian Stock Market. *Journal of Research in Emerging Markets*, 3(1), 14–31. <https://doi.org/10.30585/jrems.v3i1.555>.
- Ji, Q., Bouri, E., Gupta, R., & Roubaud, D. (2018). Network causality structures among Bitcoin and other financial assets: A directed acyclic graph approach. *The Quarterly Review of Economics and Finance*, 70, 203–213. <https://doi.org/10.1016/j.qref.2018.05.016>.
- Ji, Q., Zhang, D., & Zhao, Y. (2020). Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis*, 71, 101526.
- Jin, X. (2016). The impact of 2008 financial crisis on the efficiency and contagion of Asian stock markets: A Hurst exponent approach. *Finance Research Letters*, 17, 167–175. <https://doi.org/10.1016/j.frl.2016.03.004>
- Jin, X., & An, X. (2016). Global financial crisis and emerging stock market contagion: A volatility impulse response function approach. *Research in International Business and Finance*, 36, 179–195.
- Junttila, J., Pesonen, J., & Raatikainen, J. (2018). Commodity market based hedging against stock market risk in times of financial crisis: The case of crude oil and gold. *Journal of International Financial Markets, Institutions and Money*, 56, 255–280.
- Kajtazi, A., & Moro, A. (2018). The role of bitcoin in well diversified portfolios: A comparative global study. *International Review of Financial Analysis*, 61, 143–157.

- Karanasos, M., Yfanti, S., & Karoglou, M. (2016). Multivariate FIAPARCH modelling of financial markets with dynamic correlations in times of crisis. *International Review of Financial Analysis*, 45, 332–349.
- Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economic Letters*, 158, 3–6.
- Kostika, E., & Laopodis, N. T. (2019). Dynamic linkages among cryptocurrencies, exchange rates and global equity markets'. *Studies in Economics and Finance*, 37(2), 243–265.
- Kurka, J. (2019). Do cryptocurrencies and traditional asset classes influence each other? *Finance Research Letters*, 31, 38–46.
- Lahmiri, S. (2015). Long memory in international financial markets trends and short movements during 2008 financial crisis based on variational mode decomposition and detrended fluctuation analysis. *Physica A: Statistical Mechanics and Its Applications*, 437, 130–138.
- Lahmiri, S. (2017a). A study on chaos in crude oil markets before and after 2008 international financial crisis. *Physica A: Statistical Mechanics and Its Applications*, 466, 389–395.
- Lahmiri, S. (2017b). Cointegration and causal linkages in fertilizer markets across different regimes. *Physica A: Statistical Mechanics and Its Applications*, 471, 181–189.
- Lahmiri, S. (2017c). Asymmetric and persistent responses in price volatility of fertilizers through stable and unstable periods. *Physica A: Statistical Mechanics and Its Applications*, 466, 405–414.
- Lahmiri, S., Salah Uddin, G., & Bekiros, S. (2017a). Nonlinear dynamics of equity, currency and commodity markets in the aftermath of the global financial crisis. *Chaos, Solitons & Fractals*, 103, 342–346.
- Lahmiri, S., Salah Uddin, G., & Bekiros, S. (2017b). Clustering of short and long-term comovements in international financial and commodity markets in wavelet domain. *Physica A: Statistical Mechanics and Its Applications*, 486, 947–955.
- Li, X., & Wang, C. A. (2017). The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin. *Decision Support Systems*, 95, 49–60. <https://doi.org/10.1016/j.dss.2016.12.001>
- Lien, D., Lee, G., Yang, L., & Zhang, Y. (2018). Volatility spillovers among the U.S. and Asian stock markets: A comparison between the periods of Asian currency crisis and subprime credit crisis. *The North American Journal of Economics and Finance*, 46, 187–201.
- Maghyreh, A., & Abdo, H. (2021). Time-frequency quantile dependence between Bitcoin and global equity markets. *The North American Journal of Economics and Finance*, 56, 101355.
- Matkovskyy, R., & Jalan, A. (2019). From financial markets to Bitcoin markets: A fresh look at the contagion effect. *Finance Research Letters*, 31, 93–97.
- Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. pp. 1–9. <https://bitcoin.org/bitcoin.pdf>.
- Omane-Adjepong, M., Alagidede, P., & Akosah, N. K. (2019). Wavelet time-scale persistence analysis of cryptocurrency market returns and volatility. *Physica A: Statistical Mechanics and Its Applications*, 514, 105–120.
- Ong, B., Lee, T. M., Li, G., & Chuen, D. L. K. (2015). Evaluating the potential of alternative cryptocurrencies. In *Handbook of digital currency Bitcoin, Innovation, Financial Instruments, and Big Data* (pp. 81–135).
- Peng, Y., Albuquerque, P. H. M., de Sá, J. M. C., Padula, A. J. A., & Montenegro, M. R. (2018). The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with Support Vector Regression. *Expert Systems with Applications*, 97, 177–192.
- Perron, P. (1990). Testing for a Unit Root in a Time Series With a Changing Mean. *Journal of Business & Economic Statistics*, 8(2), 153–162. <https://doi.org/10.1080/07350015.1990.1050978>.
- Pesaran, M. H. (1997). The role of economic theory in modelling the long run. *The Economic Journal*, 107(440), 178–191.
- Pesaran, M. H., & Shin, Y. (1995). An autoregressive distributed lag modeling approach to cointegration analysis. *A revised version of a paper presented at the Symposium at the Centennial of Ragnar Frisch*, The Norwegian Academy of Science and Letters, Oslo, March 3–5.
- Pesaran, M. H., & Shin, Y. (1999). An autoregressive distributed lag modelling approach to cointegration analysis. In S. Storm (Ed.), *Econometrics and economic theory in the 20th century: The Ragnar Frisch centennial symposium, chapter 11*. Cambridge University Press.
- Pesaran, M. H., Shin, Y. & Smith, R. J. (1996). Testing for the 'Existence of a Long-run Relationship'. *Cambridge Working Papers in Economics 9622*. Faculty of Economics, University of Cambridge.

- Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationship. *Journal of Applied Econometrics*, 16, 289–326.
- Pindyck, R. (1984). Risk, inflation, and the stock market. *American Economic Review*, 74(3), 335–351. <https://www.jstor.org/stable/1804011>.
- Rosenstein, M. T., Collins, J. J., & De Luca, C. J. (1993). A practical method for calculating largest Lyapunov exponents from small data sets. *Physica D: Nonlinear Phenomena*, 65, 117–134.
- Sami, M., & Abdallah, W. (2020). How does the cryptocurrency market affect the stock market performance in the MENA region? *Journal of Economic and Administrative Sciences*. <https://doi.org/10.1108/jeas-07-2019-0078> ahead-of-print.
- Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019). Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis*, 63, 322–330.
- Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. *Festschrift in Honor of Peter Schmidt*. https://doi.org/10.1007/978-1-4899-8008-3_9
- Syriopoulos, T., Makram, B., & Boubaker, A. (2015). Stock market volatility spillovers and portfolio hedging: BRICS and the financial crisis. *International Review of Financial Analysis*, 39, 7–18.
- Szetela, B., Mentel, G., Bilan, Y., & Mentel, U. (2021). The relationship between trend and volume on the bitcoin market. *Eurasian Economic Review*, 11(1), 25–42.
- Tiwari, A. K., Cunado, J., Gupta, R., & Wohar, M. E. (2018). Volatility spillovers across global asset classes: Evidence from time and frequency domains. *The Quarterly Review of Economics and Finance*, 70, 194–202. <https://doi.org/10.1016/j.qref.2018.05.001.4>
- Trabelsi, N. (2018). Are there any volatility spill-over effects among cryptocurrencies and widely traded asset classes? *Journal of Risk and Financial Management*, 11(4), 66.
- Umar, M., Hung, N. T., Chen, S., Iqbal, A., & Jebran, K. (2020). Are stock markets and cryptocurrencies connected? *The Singapore Economic Review*, 1–16. <https://doi.org/10.1142/s0217590820470050>.
- Urquhart, A. (2016). The inefficiency of Bitcoin. *Economic Letters*, 148, 80–82.
- Urquhart, A. (2017). Price clustering in Bitcoin. *Economic Letters*, 159, 145–148.
- Wang, G.-J., Xie, C., Lin, M., & Stanley, H. E. (2017). Stock market contagion during the global financial crisis: A multiscale approach. *Finance Research Letters*, 22, 163–168.
- Xu, Y., Taylor, N., & Lu, W. (2018). Illiquidity and volatility spillover effects in equity markets during and after the global financial crisis: An MEM approach. *International Review of Financial Analysis*, 56, 208–220.
- Yang L. T. Y. (2020) The influence of Taiwan's stock market on Bitcoin's price under Taiwan's monetary policy threshold. *Applied Economics*, 52(45), 4967–4975. <https://doi.org/10.1080/00036846.2020.1751802>.
- Yi, S., Xu, Z., & Wang, G. J. (2018). Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? *International Review of Financial Analysis*, 60, 98–114.
- Zeng, T., Yang, M., & Shen, Y. (2020). Fancy Bitcoin and conventional financial assets: Measuring market integration based on connectedness networks. *Economic Modelling*, 90, 209–220.
- Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 36, 101528.
- Zhang, J. B., Gao, Y. C., & Cai, S. M. (2020). The hierarchical structure of stock market in times of global financial crisis. *Physica A: Statistical Mechanics and Its Applications*, 542, 123452. Article.

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