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Luca Gambarelli[1], Gianluca Marchi[2], Silvia Muzzioli[3]

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[1]University of Modena and Reggio Emilia, Department of Economics Marco Biagi
Email: luca.gambarelli@unimore.it
[2]University of Modena and Reggio Emilia, Department of Economics Marco Biagi
Email: gianluca.marchi@unimore.it
[3]University of Modena and Reggio Emilia, Department of Economics Marco Biagi and CEFIN
Address: Viale Berengario 51, 41121, Modena, Italy
Email: silvia.muzzioli@unimore.it

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Luca Gambarelli [a], Gianluca Marchi [b], Silvia Muzzioli[c*]

[a] *Marco Biagi Department of Economics, University of Modena and Reggio Emilia, Italy*

[b] *Marco Biagi Department of Economics, University of Modena and Reggio Emilia, Italy*

[c] *Marco Biagi Department of Economics and CEFIN, University of Modena and Reggio Emilia, Italy*

Abstract:

The aim of the paper is twofold: first, to examine the hedging effectiveness of cryptocurrencies and cryptocurrency portfolios for European equities in bearish and bullish market conditions, and second, to contrast cryptocurrencies with gold as a safe haven asset. To this end, daily data from 2018 to 2021 were employed in a linear and nonlinear Autoregressive Distributed Lag (ARDL) framework.
The findings have significant implications for investors, financial intermediaries and regulators. First, none of the cryptocurrencies under investigation acts as a safe haven for the European stock market. Second, an asymmetric relationship was found between Bitcoin / Ethereum returns on the one hand and stock market returns on the other, indicating the risk of large joint losses during periods of market turmoil. Third, cryptocurrency portfolios appear to perform better than Bitcoin and Ethereum for diversification purposes. Fourth, among cryptocurrency portfolios, the portfolio made up of the top ten cryptocurrencies appear to be the best in terms of diversification benefits and the risk-return profile. Finally, during the 2020 bear market conditions, not even gold acted as a safe haven for European stocks, highlighting the need to investigate alternative safe haven assets to mitigate portfolio risks.

Keywords: Cryptocurrencies, Hedging, Asymmetric effects, Stock market returns, Covid-19 outbreak

[*] Corresponding author: Marco Biagi Department of Economics and CEFIN, University of Modena and Reggio Emilia, Viale Berengario 51, 41121 Modena (I), Mail silvia.muzzioli@unimore.it Tel. +390592056771 Fax +390592056947,ORCID iD: 0000-0003-0738-6690.

1. Introduction

Cryptocurrencies have become increasingly popular among investors (Balcilar et al., 2017), and for a certain period were hailed by a number of authors as the "biggest financial innovation of the century" (Li et al., 2021). They have attracted increasing scrutiny on the part of investors, financial institutions, policymakers, regulators, and the media. FinTech and Blockchain are key instruments among technology leaders in finance today (Chang et al., 2020). The growing interest in cryptocurrencies is testified by the possibility of using them as a mode of payment in an increasing number of countries and the support received corporations like Tesla, Meta, Microsoft, Starbucks, Dell, Visa, and Quinn Emanuel in the US (for an in-depth analysis of the spread of cryptocurrency across countries see e.g. Bhimani et al., 2022).

Since the outbreak of the COVID-19 pandemic, the spread of cryptocurrencies, utility tokens, and security tokens has undergone a further acceleration, reaching a peak in total market value of nearly $3000 billion in November 2021. Although cryptocurrencies were not created for investment purposes, they have attracted more and more savers, especially young retail investors.[1] The increasing spread of cryptocurrencies in investor and company portfolios raises issues relating to their effectiveness in terms of portfolio diversification and hedging. There is an ongoing debate in the literature on the contribution of cryptocurrencies to a stock portfolio in terms of diversification and risk-adjusted returns. Many studies investigating the role of Bitcoin from a risk-return perspective find that cryptocurrencies have a low correlation with other asset classes, suggesting that Bitcoin might have played an active role in the diversification of portfolios. The low correlation between cryptocurrencies and traditional asset classes could be explained by their different underlying fundamentals. While economic and financial fundamentals mainly drive traditional assets, cryptocurrencies are essentially technological assets. However, some authors have gone so far as to claim that Bitcoin has characteristics comparable to gold (Baur and Hoang, 2021), in the sense that it may be considered as a store of value and similar safe haven for crypto investors. As a result, the idea that Bitcoin can be considered as a hedging asset is attracting the attention of scholars (Su et al., 2020b). Due to the fact that the returns on cryptocurrencies are characterized by very high volatility (Umar et al. 2021a) and kurtosis (Yi et al., 2022), many studies investigating the safe haven properties and spillover effects between cryptocurrencies and other assets report mixed results. To be considered a safe haven or hedge against market downturns, cryptocurrencies should be negatively related to market returns in periods characterized by turbulence and uncertainty. On the other hand, a correlation

[1] https://www.reuters.com/technology/young-uk-investors-choose-cryptocurrencies-over-stocks-survey-2021-04-22/

close to zero suggests diversification benefits of the inclusion of cryptocurrencies only in a portfolio of traditional assets. However, the existing literature fails to address this crucial point.

While some studies (see, e.g., Adediran et al., 2021) claim that Bitcoin can provide protection against uncertainty and can be considered as a safe haven asset, others detect an increasing interconnection between Bitcoin and other assets over time, resulting in a high probability of contemporaneous losses in turbulent periods (Le et al., 2021).

Most of the studies investigate the role of Bitcoin in periods characterized by a low level of volatility (mostly in the period 2012-2018). On the other hand, asset correlations tend to change dramatically during market downturns (Thampanya et al., 2020). Moreover, there appear to be no studies about the role of Bitcoin for European blue chips stocks, particularly in the period of the recent market downturn that occurred during the COVID-19 outbreak. Additionally, the majority of the papers focus on single cryptocurrencies (such as Ethereum, Bitcoin Cash, Litecoin, and Ripple) without considering the alleged diversification benefits of cryptocurrency portfolios. Finally, most of the papers do not adequately assess the dependency of financial assets during extreme bullish and bearish market conditions (Thampanya et al., 2020).

In an attempt to fill this gap, the present study focuses on the European stock market and provides new evidence on the hedging effectiveness of cryptocurrencies and cryptocurrency portfolios in a period characterized by high and low volatility phases. In particular, the paper analyses the European blue chip index (Eurostoxx 50) for the period between March 2018 and April 2021. The sample period, motivated by the availability of data for cryptocurrency portfolios, makes it possible to investigate the behaviour of cryptocurrencies for the European stock market both during bullish and bearish market phases.

In line with Bilgin et al. (2018) and Thampanya et al. (2020), the dataset (Bitcoin, Ethereum, six cryptocurrency portfolios, and Gold) was examined with an Autoregressive Distributed Lag (ARDL) and a Nonlinear ARDL model, which are particularly suitable for this kind of analysis. Moreover, the use of a nonlinear ARDL model makes it possible to assess whether positive and negative shocks in cryptocurrencies affect the stock market differently.

Five key findings were obtained.

First, none of the cryptocurrencies under investigation (two major cryptocurrencies, six cryptocurrency indices) proved to be a safe haven for the European stock market during the period 2018-2021, with Bitcoin and Ethereum found to be the most closely correlated with stock market returns in bear market phases.

Second, the NARDL model used to distinguish between positive and negative returns cast light on the existence of an asymmetric relationship between cryptocurrencies and stock market returns during bearish market phases. In particular, evidence was found of a strong positive short-term association between negative Bitcoin / Ethereum returns on the one hand and stock market returns on the other, indicating the possibility of large joint losses in the event of market turbulence.

Third, returns from cryptocurrency portfolios do not display a strong association with market returns in most phases. Although these assets do not act as a safe haven for the stock market, the lack of a strong association between negative cryptocurrency portfolio returns and stock returns suggests that these assets can be used for diversification purposes in the short term, providing higher diversification benefits compared to Bitcoin and Ethereum.

Fourth, among cryptocurrency portfolios, a basket consisting of the top ten cryptocurrencies seems sufficient to achieve the highest diversification benefit, showing a better risk-return profile compared to portfolios made up of a large number of minor cryptocurrencies.

Finally, the well-known role as a safe haven for gold is detected only during the 2018 market downturn, while it failed to act as a safe haven during the COVID-19 market downturn.

The remainder of the paper is as follows: Section 2 reviews the related literature. Section 3 outlines the dataset and the methodological approach adopted in the study. Section 4 presents and discusses the empirical results for the European stock market. Finally, Section 5 concludes and provides implications for investors, product managers, policy-makers and regulators.

2. Literature review

Many studies show that stock market correlations have increased over time (see, e.g., Frijns et al., 2017 for a literature review); thus, analysing and managing financial risks has become more and more important in an increasingly connected global market (Raddant and Kenett, 2021). The increase in correlations has been only partly attributed to growing levels of political, economic and financial integration, suggesting that financial innovation can play an important role. Financial innovation may have contributed to changing correlations between the various asset classes in two different ways. First, innovative products such as derivatives and index products have broadened investor access to various investment solutions, facilitating investment in commodities, making their price behave more and more like stocks and contributing to changing correlations and co-movements between many asset classes (Bekiros et al., 2017). Second, trading strategies have evolved towards algorithms and high-frequency trading due to the speed of profits and the possibility to automate trades. These strategies often involve contemporaneous trades on different asset classes, and the empirical evidence suggests that this may lead to increased cross-asset correlations over time (Bicchetti and Maystre, 2013). For this reason, researchers and practitioners tend to focus increasingly on the interdependence between stocks and innovative assets. In particular, they aim to assess whether cryptocurrencies can improve the investors' risk-return trade-off, or act as a safe haven asset for the stock market. In addition, a growing number of academics and researchers have tried to understand the benefits and risks that cryptocurrencies can offer for economic growth, financial system stability, and the overall welfare of society (see, e.g., Ahluwalia et al., 2020**).**

Regarding the inclusion of cryptocurrencies in investor portfolios, it is possible to broadly distinguish between two strands of literature. The first one investigates the impact of cryptocurrencies on stock returns from a risk-return perspective (e.g., including cryptocurrencies in the optimal portfolio using the Markowitz Mean-Variance analysis and the Sharpe ratio), while the second one investigates the role of cryptocurrencies as safe haven assets.

Studies in the first strand of literature generally claim that the addition of Bitcoin to a well-diversified portfolio consisting of stocks and other traditional assets (e.g. currencies, gold, oil, real estate, and bonds) can significantly improve the risk-return profile (Briere et al., 2015; Li et al., 2021). Symitsi and Chalvatzis (2019) find that the benefits arising from the inclusion of Bitcoin in the portfolio are more evident for commodities than for other traditional assets. They also claim that the high volatility of Bitcoin does not increase the overall portfolio risk due to the low correlation between Bitcoin and other assets. Kajtazi and Moro (2019) argue that by including Bitcoin, the portfolio performance improves, but the result is mainly attributable to the increase in the portfolio returns due to the positive performance of Bitcoin in 2013. More recently, concerns about the inclusion of Bitcoin in a portfolio are expressed by Symitsi and Chalvatzis (2018), since they find evidence of negative spillovers between Bitcoin and stock indices.

The improvement in the risk-return portfolio profile has been confirmed also for the inclusion in portfolios of other cryptocurrencies. Platanakis and Urquhart (2019) analyse 55 cryptocurrencies and find that the portfolio returns significantly increase compared to portfolios made up only of traditional assets. Among cryptocurrencies, Ma et al. (2020) argue that Ethereum provides a better diversification opportunity compared to Bitcoin.

While previous contributions (mainly investigating the risk-return trade-off) were almost unambiguous in affirming the superiority of portfolios that include Bitcoin compared to portfolios of traditional assets only, studies in the second strand of literature report conflicting findings on the safe haven properties of Bitcoin. In particular, several studies find evidence of return spillovers between Bitcoin and traditional assets, questioning its safe haven properties. Umar et al. (2021a) investigate return spillovers between cryptocurrencies and traditional global indices and find evidence that returns on cryptocurrencies affect returns of other indices and that investor confidence in the crypto market spilled over to other markets. Moreover, Bitcoin seems to be becoming more interconnected to other markets over the years. Akyildirim et al. (2020) find evidence of a time-varying positive interrelationship between the conditional correlations of cryptocurrencies and volatility indices, that are found to increase substantially during periods of high financial market stress. Conlon and McGee (2020) point out that the S&P 500 and Bitcoin move in lockstep, resulting in increased downside risk for an investor with an allocation in stocks and Bitcoin. The close interconnection between Bitcoin and traditional common stocks could result in contemporaneous losses in turbulent conditions (Le et al., 2021). The high probability of substantial joint losses is confirmed by Huynh et al. (2020b), due to the fact that Bitcoin and traditional assets exhibit heavy-tail dependence, and by Wang et al. (2022), who find that the left-tail dependence between Bitcoin and traditional assets is more significant than the right-tail dependence. In addition, Le et al. (2021) and Huynh et al. (2020b) report that volatility transmission is higher in the short term, suggesting that holding assets for the long term is likely to mitigate risks, whereas trading financial assets in the short term can increase risk because of higher volatility. Similarly, Kumar et al. (2022) show that the returns connectedness between cryptocurrencies and traditional financial assets is high over short-time horizons (from one day to one week), and intensified during the COVID-19 pandemic. The safe haven role of Bitcoin for the stock market has been rejected also in some emerging markets (see e.g. Thampanya et al., 2020 for the Thai stock market and Ngo and Nguyen, 2021 for the Vietnamese stock market). Finally, studies investigating the interconnections between Bitcoin and traditional asset classes during the pre-and post-Covid periods (see e.g., Rao et al., 2022) find that the contribution of Bitcoin to spillovers in other markets has increased significantly in the post-acute phase of the pandemic. As a result, the presumed diversification benefits of investing in Bitcoin are no longer sufficient for hedging purposes. According to these studies, instead of adding a long Bitcoin position for diversification purposes, a short position in Bitcoin could be more appropriate to hedge market risk (Guesmi et al., 2019).

Within the second strand of literature there are also studies supporting the role of Bitcoin and cryptocurrencies as an effective diversifier but only during certain market phases (Bouri et al., 2017a), since they are less integrated with the global system (Umar et al., 2021c). Hung (2020) find that the Bitcoin-stock market relationship is dependent on both the cycle of the stock market and the nature of shocks affecting Bitcoin. Evidence of time-variation for safe haven purposes are obtained also by Shahzad et al. (2019). However, the correlation between digital and traditional assets is weak, changing over time, and sensitive to external shocks, suggesting that cryptocurrencies may offer diversification benefits but are not suitable for hedging (Charfeddine et al., 2020).

Finally, other studies claim that Bitcoin acts as an effective hedge and safe haven asset for stocks at the sectoral level (Bouri et al., 2017b), against global uncertainty (Bouri et al., 2017c), geopolitical risks (Su et al., 2020a), and when political and economic uncertainties are on the rise in the US (Umar et al., 2021b). In addition, Bouri et al. (2020) claim that Bitcoin not only acts as a safe haven for many stock indices, but is also superior to gold and commodities because it shows smaller dependency with other assets. These studies suggest that investors can benefit from investing in Bitcoin during severe global uncertainty and complicated geopolitical patterns, and that Bitcoin can be considered as a risk-free, safe haven asset (Adediran et al., 2021; Wu et al., 2019).

A few studies investigate the role of different cryptocurrency portfolios. Borri (2019) finds that while cryptocurrencies are highly exposed to tail-risk within crypto markets, they are not exposed to tail-risk in other global markets. Moreover, they find that cryptocurrency portfolios tend to provide better risk-adjusted and conditional returns than individual cryptocurrencies. Similarly, evidence that the inclusion of multiple cryptocurrencies can reduce the portfolio risk considerably is reported by Brauneis and Mestel (2019) and Liu (2019). On the contrary, Yousaf and Ali (2020) who analyse the return and volatility spillovers between Bitcoin and Ethereum during the pre-COVID-19 and COVID-19 periods, find that the return spillovers between the different pairs of cryptocurrencies vary across the two periods. Consequently, investors in cryptocurrencies cannot obtain the maximum benefit of diversification by investing in these three pairs (i.e., Bitcoin–Ethereum, Bitcoin–Litecoin, Litecoin–Ethereum).

To sum up, most of the studies investigate the role of Bitcoin for the US stock market or other international stock and commodity markets. Most sample periods span from 2012 to 2018, a phase characterized by a bullish stock market and a low level of volatility. On the other hand, market correlations and connections change dramatically during high volatility and bearish market periods (Thampanya et al., 2020). To the best of our knowledge, there are no studies on the role of Bitcoin for European blue-chip stocks, especially during the recent market downturns that occurred during the acute phase of the COVID-19 pandemic. Additionally, most papers focus on the properties of Bitcoin and other major cryptocurrencies (such as Ethereum, Bitcoin Cash, Litecoin, and Ripple) without considering the relation between stocks and portfolios made up of different cryptocurrencies. Finally, a number of techniques adopted in the literature are not appropriate to determine the relationships between financial assets in extreme market conditions (Thampanya et al., 2020).

The present study attempts to fill this gap by providing new evidence on hedging effectiveness of different cryptocurrencies and cryptocurrency portfolios for European stocks. Using data for the period 2018-2021, the study investigates the behaviour of cryptocurrencies for the European stock market during both bullish and bearish market phases. While the majority of the papers focus on single cryptocurrencies, we shed light on the relationships between different cryptocurrency portfolios and stocks. Finally, the study adopts both a linear ARDL and a Nonlinear ARDL model to appropriately assess the asset dependencies during extreme bullish and bearish market conditions (Thampanya et al., 2020).

3. Data and methodology

This section provides an overview of the analysis on hedging effectiveness and asymmetric correlations of cryptocurrencies and cryptocurrency portfolios for the European stock market. Sections 3.1-3.2 are dedicated to the description of the econometric setting, while Sections 3.3-3.5 present the dataset and a preliminary analysis.

3.1 The Autoregressive Distributed Lag (ARDL) model

The decision to use an ARDL model in the analysis is based on two main factors. First, the ARDL model is more flexible than other traditional econometric approaches (such as the Vector Autoregression model or co-integration analysis), since it is able to deal with variables characterized by a different order of integration (Thampanya et al., 2020). Second, the ARDL model makes it possible to address the endogeneity issue, i.e., the correlation between the explanatory variable and the error term. In fact, unobserved heterogeneity or omitted variables can cause endogeneity, thus producing unreliable results (Ullah et al., 2020). On the other hand, if the ARDL model is not affected by correlation between the explanatory variables and the error terms, endogeneity is not present.[2] In particular, Pesaran and Shin (1999) argue that both serial correlation and endogeneity issues can be correctly addressed by the appropriate lag order in the ARDL model. Following Thampanya et al. (2020), the ARDL model adopted in the present study can be specified as follows:

$$y_t = \alpha + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q_j} X_{j,t-i}{}' \beta_{j,i} + \varepsilon_t \tag{1}$$

where y_t represents the current value of stock market return. Current and past values of independent variables (alternatively proxied by cryptocurrency and gold returns in the present application) are represented by X_j. As shown in Eq. (1), an ARDL model is a least-squares regression that includes lags for the dependent and the explanatory variables. The number of lags of the dependent variable (Eurostoxx 50 return) is represented by p, while the number of lags of cryptocurrency and gold returns is represented by q_j. Some of the explanatory variables in the model may skip lagged terms ($q_j = 0$): in this case, the variables are called fixed or static regressors. On the other hand, the explanatory variables with at least one lagged term are called dynamic regressors. In the present model,

[2] The results from the diagnostic test, the LM statistics, do not indicate autocorrelation in the error term as reported in Tables 4 and 6. Therefore, endogeneity does not affect the models adopted.

cryptocurrency and gold returns act as dynamic regressors of the current value of the stock market returns.

3.1.1 Long-run relationship

According to Pesaran et al. (2001), the dynamic relationship between the dependent and the explanatory variables can be estimated through an ARDL model and transformed into a long-run representation as follows:

$$\theta_j = \sum_{i=1}^{j} \hat{\beta}_{j,i} / \left(1 - \sum_{i=1}^{j} \gamma_i\right) \tag{2}$$

where θ_j estimates long-run coefficients, indicating the dependent variable long-rung response to a change in the explanatory variable.

3.1.2 Co-Integrating Relationship

Another important advantage of ARDL models with respect to traditional econometric approaches is the possibility of estimating a co-integrating system without the need to pre-specify *I(0)* or *I(1)*, where the variables included in the model can be either *I(0)* or *I(1)* (Pesaran et al., 2001). Unlike other methods, the ARDL representation does not need lag-length symmetry, thus allowing a different number of lags for each variable (Thampanya et al., 2020). Co-integrating regression of the ARDL model can be obtained by transforming Eq. (1) in terms of differences and replacing long-run coefficients from Eq. (2), as follows:

$$\Delta y_t = -\sum_{i=1}^{p-1} \gamma_{i*} \Delta y_{t-1} + \sum_{j=1}^{k} \sum_{i=0}^{q_j-1} \Delta X_{j,t-i}{}' \beta_{j,i*} - \varnothing \wedge EC_{t-1} + \varepsilon_t \tag{3}$$

where:

$$EC_t = y_t - \alpha - \sum_{j=1} X_{j,t}{}' \hat{\theta}_j$$

$$\varnothing \wedge = 1 - \sum_{i=1}^{p} \hat{\gamma}_i$$

$$\gamma_{i*} = \sum_{m=i+1}^{p} \hat{\gamma}_m$$

$$\beta_{j,i*} = \sum^{q_j} \beta_{j,m}$$

3.2 Nonlinear ARDL model

As discussed above, the ARDL model proposed by Pesaran et al. (2001) is more flexible than other traditional econometric approaches. However, positive and negative fluctuations of the independent variable have a symmetrical effect on the dependent variable (stock market returns). Recent studies in European financial markets (see, e.g. Elyasiani et al., 2021) find that stock market returns show an asymmetric response to innovations in skewness, thus highlighting the importance of disentangling positive and negative effects when investigating stock market returns. To account for the existence of nonlinearity in our dataset, the nonlinear ARDL (NARDL) model developed by Shin et al. (2014) was adopted. The NARDL model is an asymmetric extension of the linear ARDL model, whose long-run regression can be expressed as:

$$y = \alpha_0 + \delta^+ q_t^+ + \delta^- q_t^- + \alpha_1 x_1 + \xi_t \tag{4}$$

where δ^+ and δ^- represent the long-run parameters related to positive and negative return, and q_t is the return decomposed as:

$$q_t = q_0 + q_t^+ + q_t^- \tag{5}$$

where q_0 is the initial value, and q_t^+ and q_t^- are the partial sum processes of positive and negative changes in q_t. In line with Shin et al. (2014), q_t^+ and q_t^- are defined as:

$$q_t^+ = \sum_{j=1}^{t} \Delta qj^+ = \sum_{j=1}^{t} \max(\Delta q_j, 0)$$

$$q_t^- = \sum_{j=1}^{t} \Delta qj^- = \sum_{j=1}^{t} \min(\Delta q_j, 0)$$

Replacing q_t with q_t^+ and q_t^- around a single threshold value of zero, we allow for the differentiation of positive and negative changes in q_t. Therefore, in the linear ARDL model in Eq. (1), q_t is replaced by q_t^+ and q_t^- as follows:

$$\Delta y_t = \gamma_0 + \sum_{j=1}^{k} \gamma_{1j} \Delta y_{t-j} + \sum_{j=0}^{p} \gamma_{2j}{}^{+} \Delta x_{t-j}{}^{+} + \sum_{j=0}^{n} \gamma_{3j}{}^{-} \Delta x_{t-j}{}^{-} + \rho_0 y_{t-1} + \eta^+ x_{t-1}{}^{+} + \eta^- x_{t-1}{}^{-} + \omega_t \tag{6}$$

where the null hypothesis $\delta^+ = \delta^-$ tests long-run symmetry, given $\delta^+ = -\eta^+ / \rho_0$ and $\delta^- = -\eta^- / \rho_0$, and $\sum_{j=0}^{p} \gamma_{2j}{}^{+} = \sum_{j=0}^{n} \gamma_{3j}{}^{-}$ evaluates short-run additive symmetry. Last, $\gamma_{2j}{}^{+}$ and $\gamma_{3j}{}^{-}$ capture the short-run adjustment to positive and negative returns.

3.3 The European dataset

With regard to the developed markets,[3] most of the studies are concentrated on the US market and evidence concerning the European market is limited.

To fill this gap, daily closing prices were obtained for the Eurostoxx 50 index and different cryptocurrencies (Bitcoin and Ethereum) and cryptocurrency portfolios (FS Crypto 10, FS Crypto 40, FS Crypto 250, FS Crypto 300, and FS Crypto Aggregate, FS Crypto Top 50 Equal Weight).

[3] For emerging markets, see, e.g., Guesmi et al. (2019) and Thampanya et al. (2020).

Moreover, given the historical role of gold as a safe haven during market downturns, daily closing prices of gold were obtained for the sake of comparison. The data set covers the period from 28 March 2018 to 31 March 2021, and prices are recorded in Euros. All data are from the Thomson Reuters DataStream database.

As a benchmark for equity returns in the EU, the study focused on the Eurostoxx 50 Index (STOXX),[4] which is referred to as Europe's leading blue-chip index for the Eurozone,[5] since it provides a blue-chip representation of supersector leaders in the region. The index covers fifty of the largest and most liquid stocks in eight Eurozone countries: Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands and Spain, and serve as an underlying index for a wide range of investment products such as exchange-traded funds (ETFs), futures, options, and structured products worldwide. Therefore, it is the ideal candidate to represent an equity investment in the euro area. Moreover, the Eurostoxx 50 index is almost perfectly correlated with the Stoxx Europe 600 index in terms of daily returns (Elyasiani et al., 2020), suggesting that the empirical evidence on the former can be easily transferred to the latter.

As for cryptocurrencies, at the time of writing, in an extremely volatile market, Bitcoin (BTC) is the world's most popular and largest (in terms of market value) cryptocurrency. Ethereum (EHT) is the second-largest cryptocurrency by market value and daily volume.[6] Therefore, both cryptocurrencies will be taken into account in the analysis, also for the sake of comparison with previous studies. However, in order to account for the substantial number of cryptocurrencies recently introduced and to investigate the diversification benefits of a cryptocurrency portfolio, we also consider six cryptocurrency indices for tracking digital currencies recently introduced by Fundstrat.[7] These indices track a total of 630 digital currencies divided into six groups by market capitalization and trading volume:

- FS Crypto 10 (FSTOK10) that tracks the top 10 digital currencies by market value and liquidity (they include Bitcoin and Ethereum, among others);
- FS Crypto 40 (FSTOK40), that tracks the top 11 to 50 digital currencies by market value and liquidity;
- FS Crypto 250 (FSTOK250), that tracks the top 51 to 300 cryptocurrencies by market value and liquidity;

[4] Existing studies (see, e.g., Kajtazi and Moro, 2019) consider the S&P EUROPE 350 index a benchmark for investment in European stocks. Unlike the Eurostoxx 50 Index, which is the most widely used regional blue-chip index, the S&P EUROPE 350 index consists of 350 leading blue-chip companies drawn from 16 developed European markets, including companies outside the euro area.

[5] https://www.stoxx.com/index-details?symbol=sx5e

[6] https://www.reuters.com/article/us-crypto-currency-bitcoin/bitcoin-ether-hit-fresh-highs-idUSKBN2AK05X

[7] Fundstrat Global Advisors is a leading sell-side independent research firm that covers US macro strategy, portfolio strategy, digital asset analysis, quantitative analysis, technical analysis and policy analysis.

- FS Crypto 300 (FSTOK300), that tracks the 300 largest digital currencies by market value and liquidity;
- FS Crypto Aggregate (FSTOKA), that tracks the performance of 630 digital currencies.
- FS Crypto Top 50 Equal Weight (FSTOKE), which tracks the top 50 cryptocurrencies using an equal-weighting approach.

Although these indices are not already tradeable assets, they are widespread on financial information providers (Bloomberg, Financial Times, Yahoo Finance, Trading View) and their performance can be effectively used to assess the diversification benefits and hedging effectiveness of investing in a basket of cryptocurrencies with respect to a single cryptocurrency.

3.4 Descriptive statistics

Table 1 shows the descriptive statistics of daily returns of Eurostoxx 50, Bitcoin, Ethereum, six cryptocurrency portfolios, and gold, where the return is computed as the difference in the log of prices. Several observations are in order. First, all the return series related to investment in cryptocurrencies show an extremely high standard deviation of daily returns compared to traditional assets such as STOXX and GOLD. Among the series considered in our study, GOLD is the asset characterized by the lowest standard deviation. Second, the series with the highest volatility is the FS Crypto 250 index (FSTOK250), which tracks the top 51 to 300 cryptocurrencies, suggesting that also an investment in a high number of "small" cryptocurrencies can be characterized by an extreme level of volatility. Third, all the series display negative skewness and pronounced excess kurtosis, indicating that a considerable mass of the distribution is located in the left tail. Consequently, the hypothesis of a normal distribution (Jarque-Bera test) is firmly rejected for all the series.

The last three rows of Table 1 show the results of some preliminary tests adopted to evaluate the presence of unit root and cointegration relationships in the dataset. More specifically, we applied a standard unit root test, i.e., the Dickey and Fuller (1979, ADF) and the Kapetanios et al. (2003, KSS) test to exclude the presence of I(2) variables. In fact, the KSS unit root test is more powerful than the conventional unit root test (e.g., the ADF test), especially when a significant nonlinear component characterizes the data. The results of both the ADF and the KSS tests exclude I(1) variables in our dataset, and in turn of I(2) variables thus confirming that it is statistically appropriate to apply an ARDL model to the data. Finally, in the last row, the results are shown for the Kapetanios et al. (2006) cointegration test, which makes it possible to evaluate the existence of a long-term relationship between the variables against the null hypothesis of no cointegration relationship. The test, performed in pairs between STOXX and the other series, strongly rejects the hypothesis of no cointegration between STOXX returns on the one hand, and returns of cryptocurrencies and gold on the other, thus indicating the existence of a long-term relationship between the variables.

The correlation coefficients between the series of daily returns are shown in Table 2. It is interesting to note that almost all the crypto assets are positively related to each other in the period under investigation (2018-2021). Moreover, GOLD daily returns are significantly and positively related to BTC (ρ =0.156) and ETH (ρ =0.122) returns, while not being significantly related to STOXX returns and cryptocurrency portfolios. On the other hand, STOXX returns are positively and significantly correlated with both BTC (ρ =0.197) and ETH returns (ρ =0.220), suggesting that the two major cryptocurrencies may move in the same direction of the stock market. Among the six cryptocurrency indices, FSTOK300 and FSTOKA are almost perfectly correlated (ρ = 0.990 and ρ = 0.993, respectively) with FSTOK10 in terms of daily returns. The same holds for FSTOK300E, which is highly related to FSTOK40 (ρ = 0.978). Therefore, due to the difficulty of managing such a large number of cryptocurrencies in a portfolio, in the following empirical exercises, these three indices (FSTOK300, FSTOKA, FSTOKE) will not be considered.

3.5 Identifying market phases

Previous studies on asymmetric correlation between cryptocurrency and stock market returns (e.g., Thampanya et al., 2020) adopt a specific procedure (based on six points) for splitting the series into bull and bear market phases. We follow their method to detect the turning points in our dataset (we refer to Thampanya et al., 2020, for a detailed description of the procedure), while departing from it to identify the market phases during the COVID-19 outbreak market collapse. More specifically, since the collapse occurred between February and March 2020 was sudden and short-lived, we considered a slightly more extended period to have a sufficient number of observations in the subsequent analyses. The different market phases are highlighted in Figure 1, depicting the performance of the Eurostoxx 50 index along with the implied volatility measured by the VSTOXX index. The four phases are the following:

1. March 28, 2018 – December 27, 2018: a slightly bearish phase characterized by a modest level of volatility;
2. December 28, 2018 – February 17, 2020: a bullish market phase characterized by low volatility;
3. February 18, 2020 – April 21, 2020: a sudden and deep market downturn characterized by an extremely high level of volatility during the COVID-19 outbreak;
4. April 22, 2020 – March 31, 2021: a bullish market phase characterized by a level of volatility that remains moderate.

4. Empirical results

This section examines the hedging effectiveness and asymmetric correlation of cryptocurrencies and cryptocurrency portfolios for the European stock market, which is proxied by the Eurostoxx 50 index (STOXX), by implementing both the linear and nonlinear ARDL models presented in Sections 3.1 and 3.2.

4.1 ARDL model

In line with Thampanya et al. (2020), the relation between stock market, Bitcoin, Ethereum, FSTOK10, FSTOK40, FSTOK250 and gold is investigated in different market phases as defined in Section 3.5. The ARDL model is performed for each period on returns. Regarding the model settings, a maximum number of four lags is imposed on each variable, and the optimum number of lags is chosen by using the AIC (Akaike Information Criterion). Table 3 reports the results for the short-run in the four subsamples (t-stats are reported in parentheses). Several observations are in order. First, in four cases (Panels A, C, D), BTC shows a significant or marginally significant relationship with the stock market, suggesting an association between the two assets' daily returns. Similar results are obtained for ETH, positively correlated with the Eurostoxx 50 in terms of daily returns in the second part of the sample (Panels C, D). When examining the COVID-19 period (Panel C), both BTC and ETH returns (columns 1-2) show significant short-run relationships with the stock market. More specifically, the positive sign and the high magnitude of the coefficients (0.324 and 0.249 for BTC and ETH, respectively) indicate that both Bitcoin and Ethereum do not act as safe haven assets for the STOXX.

Second, all the cryptocurrency indices are uncorrelated or only marginally correlated with market returns in most cases, suggesting that the cryptocurrency portfolios are more suitable than BTC and ETH for diversification purposes. More specifically, the association of FSTOK10 with STOXX returns tends to be insignificant in all the subsamples under investigation, with the sole exception of the COVID-19 market downturn (Panel C). During this period, the relationship between contemporaneous FSTOK10 and STOXX returns is only marginally significant (at the 10% level). On the other hand, FSTOK40 returns are significantly related to STOXX returns during the bullish period following the COVID-19 outbreak, suggesting that even a high number of minor cryptocurrencies does not improve the level of diversification that can be obtained with a portfolio consisting of the top 10 cryptocurrencies. However, during the COVID-19 market downturn (Panel C), the cryptocurrency indices show a lower positive coefficient (in terms of magnitude) than BTC and ETH, thus indicating a better diversification performance during market turbulences.

Third, the relationship between GOLD and STOXX returns (reported in the last column) is mixed: the coefficient is negative during bullish market periods (Panels B and D) and positive during the COVID-19 market downturn (Panel C). Therefore, gold tends to behave as a hedge during bullish market periods (given the negative relationship with market returns), but it failed to act as a safe haven during the COVID-19 market downturn.

To sum up, BTC and ETH show significant relationships with the stock market, that strengthen during market turbulence. Therefore, BTC and ETH do not act as proper hedging or safe haven asset for European stocks. This result is in line with Thampanya et al. (2020), who find that the relationship between stocks and Bitcoin is significantly positive during the bear market period that occurred on the Thai stock market from January 2018 to December 2018. On the other hand, although cryptocurrency portfolios do not act as a hedge in terms of market returns given the absence of a negative relationship between the two variables, they could be more effective than single cryptocurrencies for diversification purposes.

In the financial literature, gold has traditionally been considered a safe haven for US stocks (Ciner et al., 2013) and equity funds (Flavin et al., 2014) due to its behaviour, especially during the global financial crisis. In fact, during turbulent periods, the correlation between gold and aggregate US stocks has usually been negative, supporting the safe haven hypothesis for gold (Junttila et al., 2018). However, some recent studies (see, e.g., Thampanya et al., 2020) reveal that stocks and gold have positive relations in most of the considered subsamples, casting doubts on its safe haven properties in recent times. The results are in line with Beckmann et al. (2015), who find that gold serves as a poor safe haven asset for several emerging stock markets. Also, Bekiros et al. (2017) suggested that gold is neither a hedge nor a safe haven asset for stocks in BRIC markets. This result can be related to the accelerated financialization of commodity markets (Huynh et al., 2020a), which has significantly increased gold investments, making the gold price behave more and more like stocks (i.e., increasing its return correlation with the stock market). Given that asymmetries are more likely to occur in bear markets than in bull markets (Thampanya et al., 2020), the role of gold will be better investigated in the following section by exploiting the NARDL model to distinguish between positive and negative returns.

Table 4 reports several tests: the LM test, used to detect potential autocorrelation in the error term, and two coefficient stability tests based on the cumulative sum of recursive residuals (CUSUM), and on the cumulative sum of squares of recursive residuals (CUSUMQ). It also shows the results of the Bounds test method, adopted to investigate the relationship between variables over the long run. Table 4 is organized in four different panels, according to the four market phases. The LM statistic, distributed as χ^2 with four degrees of freedom with a critical value of 9.48, does not indicate autocorrelation in the error term in all the models. The CUSUM and CUSUMQ plots, not reported in order to save space but available upon request, suggest that the coefficients of the variables are stable in all models. Finally, an F-test is performed for the joint significance of the coefficients of variables related to lagged levels. Co-integration implies that the variables move together, and do not diverge from the long-run equilibrium, i.e., a short-run phenomenon departure is considered a disequilibrium between variables. The null hypothesis of no long-run relationship is rejected if the F-statistic is above the upper bound critical value (I1 Bound) reported in Table 4. The obtained F-statistic for co-integration with unrestricted constant and no trend show that the null hypothesis of no long-run relationship can be rejected in all models and for all the four market phases. This result is in line with Thampanya et al. (2020) and indicates that the stock market returns have long-run relationships in both bull and bear market phases with both cryptocurrencies and gold returns.

Moreover, in line with Thampanya et al. (2020), it is not straightforward to combine the long run with the short-run results for cryptocurrencies. More specifically, while the findings suggest long-term adjustments, a short-term relationship was not detected in many cases. This result could be related to the use of a linear ARDL model. The linear assumption introduced in the linear ARDL model may cause the absence of evidence for the connections between cryptocurrency and stock returns. On the other hand, positive and negative shocks in gold or cryptocurrencies returns may affect the stock market differently. Therefore, the NARDL model described in Eq. (6) will be used in Section 4.2 to disentangle positive and negative returns and to assess the existence of an asymmetric relationship between the stock market returns on the one hand and the cryptocurrency and gold returns on the other.

4.2 The nonlinear ARDL model

In the estimation of the NARDL model in Eq. (6), the same setting previously adopted for the analysis of the linear ARDL model is used: a maximum number of four lags is imposed on each variable, and the optimum number of lags is chosen by AIC (Akaike Information Criterion). Table 5 shows the short-run nonlinear relations between the STOXX on one hand, and cryptocurrencies and gold returns on the other. The short-run effects of the positive and negative returns cryptocurrency/gold on the stock market are indicated respectively by the significance and sign of γ_{2j}^{+} and γ_{3j}^{-}. For each model, the null hypothesis of no short-run asymmetry $\sum_{j=0}^{p}\gamma_{2j}^{+}=\sum_{j=0}^{n}\gamma_{3j}^{-}$ is evaluated using a Wald test.

Given that asymmetries are more likely to occur in bear markets compared to bull markets (Thampanya et al., 2020), Table 5 reports the results of the NARDL model only for the periods characterized by a negative performance of the Eurostoxx 50, i.e., the subsample between March and December 2018 (Panel A) and the market downturn occurring during the COVID-19 outbreak (Panel

C). The results for the remaining subsamples (Panel B and Panel D, not reported in the paper for reasons of space but are available upon request) do not show any asymmetric pattern, suggesting that positive and negative cryptocurrency and gold returns have no significant different effect on the stock market during bullish market periods.

The results of the Wald test for the existence of short-run asymmetry are reported in Table 6, along with other diagnostic tests (LM test, CUSUM and CUSUMQ test) and the Bounds test for co-integration analysis. The null hypothesis of no short-run asymmetry for the bearish market period from March to December 2018 (reported in Table 5, Panel A) can be rejected only for ETH and GOLD. More specifically, negative ETH returns are associated with negative STOXX returns, while no effect is detected for positive returns. On the other hand, only positive returns on gold show a negative short-term association with STOXX returns, suggesting that GOLD acts as a safe haven for STOXX during the bearish market period that occurred in the last part of 2018. Positive BTC returns are significantly related to STOXX returns (positively), while the same is not true for BTC negative returns, suggesting that BTC was better than ETH for diversification purposes during this period.

The results for the COVID-19 outbreak, reported in Table 5, Panel C, deserve a more detailed discussion. The Wald test reported in Table 6 rejects the symmetry hypothesis for all the cryptocurrencies and the cryptocurrency portfolios under investigation, indicating that the distinction between positive and negative returns is crucial to understand the properties of cryptocurrencies as a hedge for European stocks. A strong positive short-term association is detected between negative BTC/ETH returns on the one hand and stock market returns on the other. Also, the magnitude of the relationship, equal to 0.365 and 0.262 for BTC and ETH returns, respectively, indicates the possibility of large joint losses in the event of market turbulence, supporting the ineffectiveness of both BTC and ETH as hedge or safe haven assets for STOXX.

However, during the market collapse that occurred in February-March 2020, positive cryptocurrency portfolio returns (FSTOK10, FSTOK40, FSTOK250) were significantly related to market returns (positively), while the same effect is not detected for negative returns. Although these assets do not act as a safe haven for the stock market, the lack of a strong association between negative cryptocurrency portfolio returns and stock returns, even in turbulent market periods, may suggest that these assets can be considered for diversification purposes in the short term.

Surprisingly, not even gold acted as a safe haven during the market collapse that occurred in February-March 2020. In particular, the results (Panel C, last column) reveal a positive short-term relationship between positive returns on gold and stock market returns. In contrast, a negative association is expected for safe haven assets.

Several factors may have contributed to the behaviour of GOLD during the COVID outbreak. The rise of the US dollar may have driven down the price of gold in the initial phase of the market downturn. Moreover, the gold sell-off in the second week of March is linked to margin calls. To elaborate, with stock markets falling more than they had since 1987, leveraged investors were probability forced to liquidate their holdings, including gold, in order to meet margin requirements and maintain their portfolio positions.[8]

To sum up, none of the crypto assets under investigation (BTC, ETH and three cryptocurrency portfolios) proved to be a safe haven asset for STOXX. In particular, both the BTC and ETH negative returns are strongly correlated with stock market downturns, making the two major cryptocurrencies not suitable in terms of portfolio diversification. One possible reason for the strong correlation of BTC with the stock market could be the availability of a listed Bitcoin futures contract on the CME (Chicago Mercantile Exchange & Chicago Board of Trade), which makes Bitcoin more integrated into the traditional financial market and easier to short sell compared to minor cryptocurrencies.

On the other hand, negative returns from cryptocurrency portfolios do not reveal a strong association with market returns, suggesting that they might be at least useful for investors' diversification purposes. In terms of the composition of the cryptocurrency portfolios, a basket made up of the top ten cryptocurrencies seems sufficient to achieve some diversification benefit, especially during bear market periods. Moreover, the portfolio that tracks the top ten cryptocurrencies is characterized by the highest average return compared to other cryptocurrency portfolios and lower volatility than the other two portfolios FSTOK40 and FSTOK250. Finally, the behaviour of GOLD during the 2020 market downturn points to the need for alternative safe haven assets during market downturns.

5. Conclusions

This paper investigated hedging effectiveness and asymmetric correlations of different cryptocurrencies, cryptocurrency portfolios and gold for the European stock market. From the investor point of view, it is essential to assess whether these innovative investment opportunities can provide benefits in the mitigation of portfolio risks. Changes and increasing market correlations over time (see, e.g., Frijns et al., 2017) have posed crucial challenges for investors, who seek to identify financial assets that can retain or even gain value during periods of market turbulence.

In this context, this study examined safe haven properties of cryptocurrencies and cryptocurrency portfolios and contrast them with gold as a benchmark. As a reference for European

[8] https://www.spglobal.com/marketintelligence/en/news-insights/research/collateral-margin-calls-currency-and-fear-covid-19-impact-on-gold

stocks, the Eurostoxx 50 index was used, covering fifty of the largest and most liquid stocks (blue-chip) in eight Eurozone countries. Following Thampanya et al. (2020), the study applied to the dataset both linear and nonlinear ARDL models for investigating the relationships between stocks and innovative assets in bearish and bullish markets. Using a nonlinear ARDL model allows us to assess whether positive and negative returns of cryptocurrencies may affect the stock market differently. The following findings were obtained.

First, none of the crypto assets under investigation (Bitcoin, Ethereum and the six cryptocurrency portfolios) proved to be a safe haven for the Eurostoxx 50 during the period 2018-2021, with Bitcoin and Ethereum found to be the most closely correlated with stock market returns. In particular, the results highlight that both Bitcoin and Ethereum show significant relationships with the stock market in three of the four market phases.

Second, the NARDL model used to disentangle positive and negative returns shed light on the existence of an asymmetric relationship between cryptocurrencies and stock market returns during bearish market phases. More specifically, a strong positive short-term association was detected between negative BTC/ETH returns on the one hand and stock market returns on the other, indicating the possibility of large joint losses in the event of market turbulence. Therefore, in line with Guesmi et al. (2019), a short position on Bitcoin or Ethereum can be exploited as a hedge for European stocks during bearish periods

Third, unlike Bitcoin and Ethereum, cryptocurrency portfolios are unrelated or only marginally related with market returns in most cases, suggesting that the cryptocurrency portfolios are more suitable than Bitcoin and Ethereum for diversification purposes. The lower association of a cryptocurrency portfolio with market returns could be related to different investor perceptions of the cryptocurrencies that compose it. Suppose one or more cryptocurrencies feature positive news about its fundamentals or the underlying technologies. In that case, it can receive more investor support and gaining momentum even in a turbulent market period and consequently improve the overall portfolio performance.

Fourth, as regards the composition of the cryptocurrency portfolios, a basket made of the top ten cryptocurrencies achieves the highest diversification benefit among cryptocurrency portfolios, and show a better risk-return profile compared to portfolios made up of a large number of minor cryptocurrencies.

Finally, the results reveal that gold acted as a safe haven during the bear market in 2018 but not during the COVID-19 related downturn in 2020, raising a crucial question for investors. If gold cannot be a safe haven or is a safe haven asset for European stocks only during certain phases, then alternative safe haven investments should be investigated.

We believe that the results of the paper are of interest to investors, financial intermediaries, and regulators. Investors could exploit the results for asset allocation purposes or to improve forecasting models. The findings imply that adding a single cryptocurrency to a stock portfolio does not provide effective hedging during market downturns. However, adding a mix of cryptocurrencies to a stock portfolio could lead to some diversification benefits. In particular, given the speculative characteristics of cryptocurrencies and their enormous volatility, the investor exposure to these assets should be view more as an opportunity to increase portfolio return than an insurance against downside risks. As suggested by Petukhina et al. (2021), cryptocurrencies can improve the risk-return profile of portfolios, but their investment benefit depends on investor objectives and characteristics.

Future research should constantly monitor the evolution of the interrelation between cryptocurrencies and traditional asset classes over time. For instance, researchers could examine whether the recent introduction of cryptocurrency-based derivative contracts could mitigate the volatility of these assets. In addition, as suggested by Wang et al. (2022), the increasing number of investors adding cryptocurrencies to their investment portfolios could result in a stronger connection between cryptocurrencies and traditional markets. Further studies are also needed to investigate possible connections between the investment opportunities provided by the fourth industrial revolution and the different industry-specific indices of the stock market, such as the technology sector, which has gained increasing importance in investor portfolios since the onset of the pandemic.

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Table 1 – Descriptive statistics and preliminary tests

	STOXX	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	FSTOK300	FSTOKA	FSTOKE	GOLD
Ann. Average	5.446%	67.049%	49.627%	54.063%	30.616%	34.356%	52.307%	51.635%	19.711%	9.618%
Ann. std. dev.	21.451%	76.932%	96.496%	74.666%	85.110%	111.408%	74.165%	74.958%	87.062%	13.324%
Skewness	-1.46971	-0.39757	-0.36246	-1.19189	-0.98450	0.52778	-1.34690	-1.27275	-1.04535	-0.77976
Kurtosis	18.19441	12.04378	4.98585	14.77388	11.29820	57.32677	15.23813	14.68919	13.43491	5.74002
Jarque-Bera	10779***	4620***	804***	7105***	4172***	104356***	7598***	7052***	5865***	1121***
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
ADF (1979)	-10.959***	-12.056***	-11.613***	-11.752***	-11.599***	-13.022***	-11.657***	-11.784***	-12.107***	-14.271***
KSS (2003)	-4.917***	-2.299*	-4.294***	-4.277***	-4.737***	-3.925**	-4.365***	-4.309***	-5.053***	-3.852***
KSS (2006)	-	-4.570***	-4.223***	-5.485***	-5.651***	-5.261***	-5.555 ***	-5.517***	-5.580***	-4.987***

Note: the table shows the descriptive statistics of daily returns (in Euros) for the different series in our sample: Eurostoxx 50 (STOXX), Bitcoin (BTC), Ethereum (ETH), gold (GOLD), and the following digital currency tracker indices (cryptocurrency portfolios):

- FS Crypto 10 (FSTOK10), that tracks the 10 largest and most liquid digital currencies;
- FS Crypto 40 (FSTOK40), that tracks the top 11 to 50 digital currencies by market value and liquidity;
- FS Crypto 250 (FSTOK250), that tracks the top 51 to 300 cryptocurrencies by market value and liquidity;
- FS Crypto 300 (FSTOK300), that tracks the 300 largest digital currencies by market value and liquidity;
- FS Crypto Aggregate (FSTOKA), that tracks the performance of 630 digital currencies.
- FS Crypto Top 50 Equal Weight (FSTOKE), which tracks the top 50 cryptocurrencies using an equal weighting approach.

The average return and the standard deviation are annualized and reported in percentage terms for sake of comparison. The total number of daily returns for each series is equal to 1099 observations.

Table 2- Correlation table

	STOXX	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	FSTOK300	FSTOKA	FSTOKE	GOLD
STOXX50	1.000	0.197***	0.220***	0.075**	0.115***	0.075**	0.083**	0.080**	0.102***	0.030
BTC		1.000	0.715***	0.340***	0.350***	0.230***	0.346***	0.345***	0.340***	0.156***
ETH			1.000	0.355***	0.376***	0.268***	0.363***	0.362***	0.373***	0.122***
FSTOK10				1.000	0.869***	0.643***	0.992***	0.997***	0.887***	0.025
FSTOK40					1.000	0.658***	0.875***	0.896***	0.976***	0.009
FSTOK250						1.000	0.684***	0.688***	0.684***	-0.004
FSTOK300							1.000	0.991***	0.882***	0.019
FSTOKA								1.000	0.913***	0.023
FSTOKE									1.000	0.010
GOLD										1.000

Note: the table shows the correlation between the series of daily returns. For a definition of the series, see Table 1. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Table 3 - Linear ARDL models: short-run coefficient estimates.

	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	GOLD
Panel A: March 28, 2018 – December 27, 2018						
STOXX (-1)	-0.059 (-0.813)	-0.056 (-0.764)	-0.056 (-0.765)	-0.054 (-0.730)	-0.065 (-0.880)	-0.049 (-0.666)
STOXX (-2)	0.137* (1.881)	0.121 (1.666)	0.120 (1.645)	0.119 (1.633)	0.121* (1.667)	0.114 (1.572)
STOXX (-3)						
STOXX (-4)						
X	0.022** (2.040)	0.014 (1.578)	0.014 (1.160)	0.007 (0.785)	0.011 (1.604)	-0.123 (-1.095)
X (-1)						
X (-2)						
X (-3)						
X (-4)						
Panel B: December 27, 2018 – February 17, 2020						
STOXX (-1)	-0.005 (-0.092)	-0.003 (-0.043)	-0.002 (-0.037)	-0.002 (-0.026)	-0.002 (-0.041)	-0.023 (-0.393)
STOXX (-2)	-0.094 (-1.602)	-0.094 (-1.600)	-0.093 (-1.587)	-0.092 (-1.580)	-0.095 (-1.626)	-0.086 (-1.512)
STOXX (-3)						
STOXX (-4)						
X	-0.013 (-1.179)	0.003 (0.323)	0.000 (0.028)	0.015 (1.200)	0.022 (1.519)	-0.290*** (-3.957)
X (-1)						
X (-2)						
X (-3)						
X (-4)						
Panel C: February 18, 2020 – April 21, 2020						
STOXX (-1)	0.047 (0.366)	0.074 (0.571)	-0.305 (-1.577)	-0.279 (-1.444)	-0.271 (-1.419)	-0.065 (-0.457)
STOXX (-2)						
STOXX (-3)						
STOXX (-4)						
X	0.324*** (4.839)	0.249*** (4.771)	0.148* (1.860)	0.138* (1.802)	0.140* (1.773)	0.989*** (3.290)
X (-1)			0.125* (1.795)	0.117* (1.756)	0.118 (1.681)	
X (-2)			0.067 (1.000)	0.046 (0.707)	0.060 (0.879)	
X (-3)			0.146** (2.277)	0.137** (2.207)	0.151** (2.332)	
X (-4)						
Panel D: April 21, 2020 - March 31, 2021						
STOXX (-1)	0.005 (0.077)	0.009 (0.141)	-0.003 (-0.045)	-0.011 (-0.180)	-0.001 (-0.016)	-0.020 (-0.310)
STOXX (-2)	0.121* (1.910)	0.121* (1.918)	0.132** (2.076)	0.133** (2.100)	0.132** (2.078)	0.129** (2.065)
STOXX (-3)	-0.142** (-2.333)	-0.146** (-2.300)	-0.150** (-2.331)	-0.162** (-2.535)	-0.148** (-2.304)	-0.150** (-2.390)
STOXX (-4)						
X	0.040* (1.899)	0.032** (2.130)	0.009 (0.399)	0.037** (2.054)	-0.001 (-0.067)	-0.286*** (-3.267)
X (-1)						
X (-2)						
X (-3)						
X (-4)						

Note: The table shows the estimated short-run coefficients for the linear ARDL model described in Eq. (1). The 1%, 5%, and 10% significance levels are indicated by *, **, and ***, respectively. For a definition of the series, see Table 1.

Table 4 – Linear ARDL models: diagnostic tests for the short run and bounds test for co-integration

	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	GOLD
Panel A: March 28, 2018 – December 27, 2018						
LM test	2.608	2.600	2.447	2.395	2.773	2.368
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Stable	Stable	Stable	Stable	Stable	Stable
F-statistic	27.253	26.737	26.199	25.856	26.775	26.130
I0 Bound	3.620	3.620	3.620	3.620	3.620	3.620
I1 Bound	4.160	4.160	4.160	4.160	4.160	4.160
Panel B: December 27, 2018 – February 17, 2020						
LM test	1.409	1.418	1.995	1.802	1.487	1.214
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Stable	Stable	Stable	Stable	Stable	Stable
F-statistic	58.695	58.004	57.949	58.712	59.187	66.352
I0 Bound	3.620	3.620	3.620	3.620	3.620	3.620
I1 Bound	4.160	4.160	4.160	4.160	4.160	4.160
Panel C: February 18, 2020 – April 21, 2020						
LM test	1.771	2.533	0.398	0.654	1.470	1.791
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Stable	Stable	Stable	Stable	Stable	Stable
F-statistic	30.474	30.022	15.414	14.794	14.994	21.776
I0 Bound	3.620	3.620	3.620	3.620	3.620	3.620
I1 Bound	4.160	4.160	4.160	4.160	4.160	4.160
Panel D: April 21, 2020 - March 31, 2021						
LM test	2.789	1.940	7.253	2.865	8.297	7.734
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Rather Stable	Rather Stable	Rather Stable	Rather Stable	Rather Stable	Rather Stable
F-statistic	31.484	31.913	29.900	31.766	29.829	34.734
I0 Bound	3.620	3.620	3.620	3.620	3.620	3.620
I1 Bound	4.160	4.160	4.160	4.160	4.160	4.160

Note: The table shows the tests for the linear ARDL model described in Eq. (1), where the independent variable is alternatively proxied by BTC, ETH, FSTOK10, FSTOK40, FSTOK250, and GOLD. The results of the corresponding cryptocurrency and gold short-run coefficient estimates are arranged in Table 3. LM test is the test statistic for serial correlation (critical value of 9.48), CUSUM is the stability test result based on the cumulative sum of recursive residuals. CUSUMQ is the stability test result based on the cumulative sum of squares of recursive residuals. F-statistic refers to the Bounds test method used to evaluate the long-run (I0 is the lower bound and I1 is the upper bound).

Table 5 – Nonlinear ARDL model: short-run coefficient estimates.

	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	GOLD
Panel A: March 28, 2018 – December 27, 2018						
STOXX (-1)	-0.052	-0.068	-0.056	-0.054	-0.068	-0.055
	(-0.718)	(-0.937)	(-0.762)	(-0.722)	(-0.913)	(-0.771)
STOXX (-2)	0.126*	0.127*	0.120*	0.132*	0.121	
	(1.729)	(1.772)	(1.654)	(1.771)	(1.635)	
STOXX (-3)						
STOXX (-4)						
X+	0.041**	-0.017	0.005	-0.015	-0.006	-0.570***
	(2.326)	(-1.108)	(0.251)	(-0.755)	(-0.312)	(-3.030)
X+ (-1)				-0.009		
				(-0.510)		
X+ (-2)				0.038**		
				(2.191)		
X+ (-3)						
X+ (-4)						
X -	-0.005	0.041**	0.021	0.019	0.017*	0.357*
	(-0.343)	(2.858)	(1.100)	(1.269)	(1.937)	(1.777)
X - (-1)				0.023	0.024	
				(1.431)	(1.611)	
X - (-2)				-0.020	-0.007	
				(-1.264)	(-0.465)	
X - (-3)				-0.023	-0.030**	
				(-1.550)	(-2.041)	
X - (-4)						

	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	GOLD
Panel C: February 18, 2020 – April 21, 2020						
STOXX (-1)	-0.102	-0.051	-0.028	-0.226	0.014	-0.254
	(-0.665)	(-0.332)	(-0.133)	(-1.132)	(0.072)	(-1.688)
STOXX (-2)	-0.167	-0.171				
	(-1.045)	(-1.045)				
STOXX (-3)	-0.063	-0.080				
	(-0.430)	(-0.549)				
STOXX (-4)	0.279*	0.308**				
	(1.955)	(2.209)				
X+	0.215	0.285*	0.460***	0.521***	0.423**	1.423**
	(1.170)	(2.027)	(2.763)	(2.941)	(2.401)	(2.506)
X+ (-1)	0.152	0.232	0.082	0.132	0.024	1.616**
	(0.816)	(1.577)	(0.443)	(0.663)	(0.124)	(2.712)
X+ (-2)	0.068	0.020	0.463***	0.506	0.556***	0.679
	(0.378)	(0.135)	(2.892)	(2.960)	(3.303)	(1.300)
X+ (-3)	0.474***	0.345**		0.219		1.529***
	(2.804)	(2.425)		(1.276)		(2.987)
X+ (-4)						
X -	0.365***	0.262***	-0.038	0.001	-0.007	0.246
	(3.830)	(3.807)	(-0.441)	(0.015)	(-0.086)	(0.408)
X - (-1)			0.123*	0.129*	0.143	-1.243*
			(1.703)	(1.892)	(1.981)	(-2.023)
X - (-2)			-0.099	-0.077	-0.117	
			(-1.220)	(-1.009)	(-1.459)	
X - (-3)			0.175**	0.160**	0.217***	
			(2.434)	(2.223)	(3.022)	
X - (-4)			-0.092		-0.093	
			(-1.276)		(-1.334)	

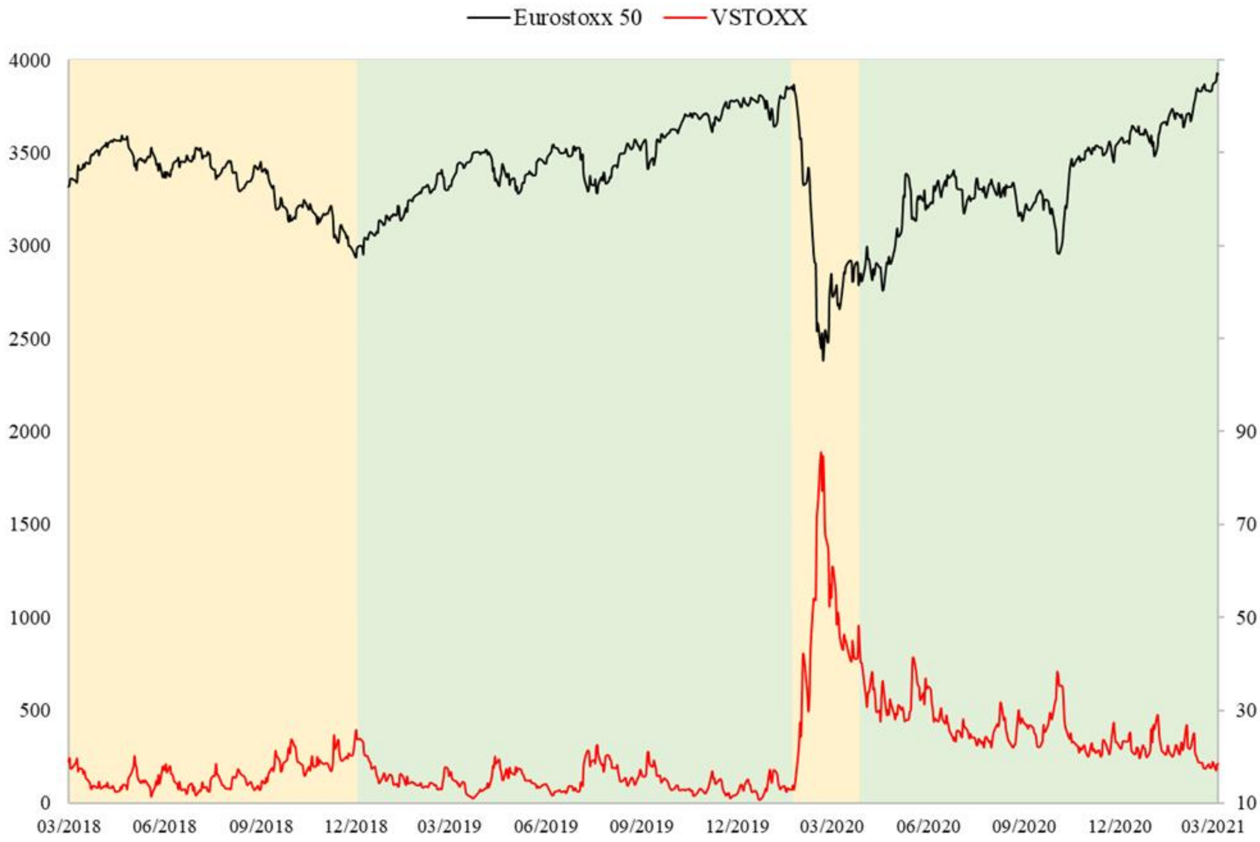
Note: The table shows the estimated short-run coefficients for the NARDL model described in Eq. (6). The 1%, 5%, and 10% significance levels are indicated by *, **, and ***, respectively. For a definition of the series, see Table 1.

Table 6 – Nonlinear ARDL models: diagnostic tests for the short run and bounds test for co-integration

	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	GOLD
Panel A: March 28, 2018 – December 27, 2018						
LM test	2.056	3.752	2.957	1.770	1.987	3.002
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Stable	Stable	Stable	Stable	Stable	Stable
Wald test χ^2	1.895	5.649	0.241	0.110	0.108	8.434
Probability	0.169	0.018	0.623	0.741	0.742	0.004
F-statistic	21.215	21.964	19.630	19.174	20.330	55.974
I0 Bound	3.100	3.100	3.100	3.100	3.100	3.100
I1 Bound	3.870	3.870	3.870	3.870	3.870	3.870
Panel C: February 18, 2020 – April 21, 2020						
LM test	4.940	3.917	2.210	1.603	2.310	6.566
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Stable	Stable	Stable	Stable	Stable	Stable
Wald test χ^2	4.110	9.056	6.961	8.262	6.419	11.181
Probability	0.043	0.003	0.008	0.004	0.011	0.001
F-statistic	8.790	8.663	8.005	9.749	7.932	18.780
I0 Bound	3.100	3.100	3.100	3.100	3.100	3.100
I1 Bound	3.870	3.870	3.870	3.870	3.870	3.870

Note: the table shows several tests for the linear ARDL model described in Eq. (6), where the independent variable is alternatively proxied by BTC, ETH, FSTOK10, FSTOK40, FSTOK250, and GOLD. The results of the corresponding cryptocurrency and gold short-run coefficient estimates are displayed in Table 5. LM test is the test statistic for serial correlation (critical value of 9.48), CUSUM is the stability test result based on the cumulative sum of recursive residuals. CUSUMQ is the stability test result based on the cumulative sum of squares of recursive residuals. Wald test is the χ^2 statistic used to evaluate the short-run asymmetry hypothesis (associated probability is reported below). F-statistic refers to the Bounds test method used to evaluate the long-run (I0 is the lower bound and I1 is the upper bound).

Figure 1 – Comparison between Eurostoxx50 index and VSTOXX implied volatility index



Note: The Eurostoxx 50 index is shown in the values on the left, while VSTOXX implied volatility is shown in the values on the right. The shaded areas in the figure represent the different bullish and bearish market periods identified in Section 3.5.