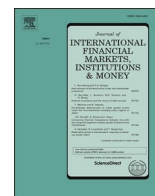


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Hedging effectiveness of cryptocurrencies in the European stock market

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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 2022 were employed in a linear and nonlinear Autoregressive Distributed Lag (ARDL) framework. The findings have significant implications for investors, financial intermediaries and regulators.

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 from 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. Despite the crisis of many players in the crypto market in the past year and the sharp contraction in terms of total market value, crypto continues to grow with more than 22,000 cryptocurrencies traded on about 530 exchanges in December 2022.¹ Although cryptocurrencies were not created for investment purposes, they have attracted more and more savers, especially young retail investors.² 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 stock portfolios 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.

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¹ Data retrieved from <https://coinmarketcap.com/>.

² <https://www.reuters.com/technology/young-uk-investors-choose-cryptocurrencies-over-stocks-survey-2021-04-22/>.

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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 touted as essentially technological assets. However, some authors have even gone so far as to claim that Bitcoin has characteristics comparable to gold (Baur and Hoang, 2021), in the sense that it might even 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 attention (Su et al., 2020b). Due to the fact that the returns on cryptocurrencies are characterized by extremely 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 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). However, 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-chip stocks, particularly in the recent market downturn that occurred during the COVID-19 outbreak and the 2022 bear market. Additionally, the majority of the papers focus on specific 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 September 2022. 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 particular, the study includes both the Bitcoin all-time high of around \$69,000 reached in November 2021 (at the peak of total cryptocurrency market value) and the sharp drop that occurred in the first half of 2022. In line with Bilgin et al. (2018) and Thampanya et al. (2020), the dataset (Bitcoin, Ethereum, Tether, six cryptocurrency portfolios, and Gold) was examined with an Autoregressive Distributed Lag (ARDL) and a Nonlinear ARDL model, which are particularly well suited to 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.

Six key findings were obtained. First, among the crypto assets under investigation (two major cryptocurrencies, six cryptocurrency indices, and Tether), only the US dollar-pegged coin Tether proved to be a safe haven for the European stock market in two out of the three bearish market phases, with Bitcoin and Ethereum found to be the most closely correlated with stock market returns in bear market phases. Second, the NARDL model adopted 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 could 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. Fifth, the well-known role of gold as a safe haven is detected only in two out of three bearish market phases (during the 2018 and 2022 market downturns). Gold failed to act as a safe haven during the COVID-19 market downturn. Finally, the five major stock markets of the Euro area (Germany, France, the Netherlands, Spain, and Italy) present similar results to those obtained for the Eurostoxx 50, highlighting the fact that despite country-specific factors such as different economic conditions and fluctuations of stock market indices, cryptocurrencies are similarly related to stock indices across European countries.

Our contribution to the literature is as follows. First, we provide new and insightful findings on the relationship between cryptocurrencies and the European stock market in a very active phase for this market, characterized by sharp increases and decreases in price. Second, we cast light on the asymmetric effects in the relationship between cryptocurrencies and stock market returns, which investors should carefully consider during bearish market periods. Third, we go beyond the analysis of individual cryptocurrencies by exploring the diversification benefits of cryptocurrency portfolios. Fourth, we clarify the role of gold and US-pegged stablecoins as a safe haven for the European stock market. Finally, we investigate how the results obtained for the Eurostoxx 50 can be compared to country-specific markets, by investigating five major European markets: Germany, France, the Netherlands, Spain, and Italy, in that order.

The remainder of the paper is structured 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. Section 5 focuses on the five major stock markets in the Euro area. Finally, Section 6 concludes and considers the implications for investors, product managers, policymakers 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 risk 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 algorithmic and high-frequency trading due to the speed of profits and the possibility to automate trades. These strategies often involve contemporaneous trades in 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 investigated 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 role 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 an 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 ([Brière 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 portfolio returns due to the positive performance of Bitcoin in 2013. More recently, serious 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 than 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, finding 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 increasingly 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 might 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 \(2021\)](#) 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 is reported also by [Shahzad et al. \(2019\)](#). However, the correlation between digital and traditional assets is weak, changing over time, and highly susceptible 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 even be considered as a risk-free, safe-haven asset (Adediran et al., 2021; Wu et al., 2019). Despite the extensive literature on the role of Bitcoin and other major cryptocurrencies and common regimes in the dynamics of cryptocurrencies (Figá-Talamanca et al., 2021a, 2021b), only a few studies investigate the role of different cryptocurrency portfolios in terms of diversification properties. Borri (2019) finds 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). In contrast, 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 and the first half of 2022. 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, stablecoins and portfolios made up of different cryptocurrencies. Finally, a number of techniques adopted in the literature are not appropriate to determine the relationship 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 2018–2022, 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 individual cryptocurrencies, we shed light on the relationships between stablecoin, 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 cointegration 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. In particular, Pesaran and Shin (1999) argue that both serial correlation and endogeneity issues can be properly 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:

$$y_t = \alpha + \sum_{i=1}^p \gamma_i y_{t-i} + \sum_{j=1}^k \sum_{i=0}^{q_j} X_{j,t-i} \beta_{j,i} + \varepsilon_t \quad (1)$$

where y_t represents the current value of stock market return. Current and past values of independent variables (alternatively proxied by crypto assets 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 crypto assets 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, 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:

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

where θ_j estimates long-run coefficients, indicating the dependent variable long-run 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:

$$\Delta y_t = - \sum_{i=1}^{p-1} \gamma_{i^*} \Delta y_{t-i} + \sum_{j=1}^k \sum_{i=0}^{q_j-1} \Delta X_{j,t-i} \hat{\beta}_{j,i^*} - \varnothing^E C_{t-1} + \varepsilon_t \tag{3}$$

where:

$$EC_t = y_t - \alpha - \sum_{j=1}^p X'_{j,t} \theta_j^{\wedge}$$

$$\varnothing = 1 - \sum_{i=1}^p \gamma_i^{\wedge}$$

$$\gamma_{i^*} = \sum_{m=i+1}^p \gamma_m^{\wedge}$$

$$\hat{\beta}_{j,i^*} = \sum_{q_j} \hat{\beta}_{j,m}$$

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:

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

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

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 . As a result, 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, γ_{2j}^+ and γ_{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 whereas evidence concerning the European market is limited. To fill this gap, daily closing prices were obtained for the Eurostoxx 50 index, two cryptocurrencies (Bitcoin and Ethereum), the stablecoin Tether (USDT) and cryptocurrency portfolios (FS Crypto 10, FS Crypto 40, FS Crypto 250, FS Crypto 300, FS Crypto Aggregate, and FS Crypto Top 50 Equal Weight). 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. Finally, to assess the validity of the results obtained for the Eurostoxx 50 index in other major markets in the Euro area, we obtain daily closing prices of stock market indices for Germany, France, the Netherlands, Spain, and Italy. The data set covers the period from 28 March 2018 to 29 September 2022, and prices are recorded in Euros. All data are retrieved 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 50 of the largest and most liquid stocks in eight Eurozone countries: Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands and Spain, and serves as an underlying index for a wide range of investment products such as exchange-traded funds (ETFs), futures, options, and structured products worldwide. As a result, 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. A more detailed analysis of how the results obtained for the Eurostoxx 50 can be compared to country-specific markets is provided in Section 5.

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, these two cryptocurrencies will be taken into account in the analysis, also for the sake of comparison with previous studies. Given that recent studies by Baur and Hoang (2021b) and Grobys et al. (2021) found evidence that stablecoins act as a safe haven against large negative price changes in Bitcoin, we include in the analysis the most common type of stablecoin, i.e., the US dollar-pegged coin Tether (USDT), to shed light on the relationship between stablecoins, the other cryptocurrencies and the European stock market. Moreover, 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 value 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;
- 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), that tracks the top 50 cryptocurrencies using an equal-weighting approach.

Although these indices are not already tradeable assets, they are made available by 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 particular cryptocurrency.

3.4. Descriptive statistics

Table 1 shows the descriptive statistics of daily returns of Eurostoxx 50, Bitcoin, Ethereum, six cryptocurrency portfolios, Tether, 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 the US dollar-pegged coin Tether (USDT) and traditional assets such as STOXX and GOLD. Among the series considered in our study, USDT is the asset characterized by the lowest standard deviation, and its price changes reflect mainly fluctuations in the exchange rate between the Euro and the US dollar.

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

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

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.

Table 1
Descriptive statistics and preliminary tests.

	STOXX	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	FSTOK300	FSTOKA	FSTOKE	USDT	GOLD
Ann. Average	-0.250 %	24.488 %	28.852 %	20.728 %	7.674 %	9.721 %	19.980 %	19.709 %	0.290 %	5.078 %	9.678 %
Ann. std. dev.	21.154 %	73.759 %	94.155 %	75.559 %	88.602 %	108.987 %	75.290 %	75.684 %	91.299 %	11.729 %	13.188 %
Skewness	-1.065	-0.399	-0.506	-0.980	-1.065	0.704	-1.148	-1.106	-1.162	0.937	-0.632
Kurtosis	16.681	12.961	7.728	13.867	13.559	48.946	14.505	14.307	15.234	19.112	7.859
Jarque-Bera	9238***	4823***	1128***	5889***	5604***	102043***	6647***	6410***	7489***	12705***	1217***
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ADF (1979)	-13.815***	-14.941***	-14.460***	-14.251***	-14.349***	-15.566***	-14.152***	-14.224***	-14.740***	-17.660***	-16.504***
KSS (2003)	-5.564***	-2.900***	-6.341***	-5.157***	-6.932***	-4.221***	5.419***	-5.380***	-7.211***	-3.265***	-4.167***
KSS (2006)	-	-5.271***	-4.917***	-5.870***	-5.845***	-5.743***	-5.886***	-5.868***	-5.785***	-5.579***	-5.454***

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), Tether (USDT), 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 annualised and reported in percentage terms for the sake of comparison. The total number of daily returns for each series is equal to 1159 observations.

volatility. Moreover, there is no benefit in terms of lower volatility when considering a portfolio made up of multiple cryptocurrencies with respect to an investment in Bitcoin, that has the lowest volatility among cryptocurrencies and cryptocurrency portfolios. In the same vein, cryptocurrency portfolios (FSTOK10, FSTOK300, FSTOKA, FSTOKE), are characterized by lower volatility with respect to an investment in Ethereum (ETH). 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 (2018–2022). Moreover, GOLD daily returns are weakly related to BTC ($\rho = 0.085$), ETH ($\rho = 0.068$) and USDT ($\rho = 0.087$) 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 ($\rho = 0.215$) and ETH returns ($\rho = 0.239$), suggesting that the two major cryptocurrencies may move in the same direction as the stock market. On the other hand, the six cryptocurrency portfolios (FSTOK10, FSTOK40, FSTOK250, FSTOK300, FSTOKA, FSTOKE) are not significantly related to STOXX. This result suggests that an investment in a cryptocurrency portfolio might produce benefits in terms of diversification compared to an investment in one of the two major cryptocurrencies (BTC and ETH). Among the six cryptocurrency indices, FSTOK300 and FSTOKA are almost perfectly correlated ($\rho = 0.990$ and $\rho = 0.994$, respectively) with FSTOK10 in terms of daily returns. The same holds for FSTOKE, which is highly related to FSTOK40 ($\rho = 0.978$). 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) are not 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. The methodology is based on a variant of the well-grounded National Bureau of Economic Research (NBER) rule⁸ for dating the business cycle, consisting of a set of filters and rules to locate the alternating turning points, i.e., peaks and troughs, of the stock market, subject to certain constraints (i.e., complete cycles implied by the turning points are required to have certain minimum and maximum durations). The methodology, commonly referred to as “turning point dating rule”, has been extensively used in the economic and financial literature (see e.g., Nyberg 2013 for a literature review). Alternative methodologies adopted in the literature to investigate the relationship between financial assets in different market conditions divide up the sample period based on volatility (see e.g., Elyasiani and Muzzioli, 2022). However, for a more detailed analysis of the phases⁹ and for ease of comparison with previous work on the subject, we follow Thampanya et al. (2020) to detect the turning point in our dataset (we refer to Thampanya et al., 2020, for a detailed description of the procedure). The different market phases are highlighted in Fig. 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. 28 March 2018 – 27 December 2018: a bearish market phase characterized by a modest level of volatility;
2. 28 December 2018 – 17 February 2020: a bullish market phase characterized by low volatility;
3. 18 February 2020 – 30 October 2020: a bearish market phase characterized by an extremely high level of volatility during the COVID-19 outbreak;
4. 2 November 2020 – 16 November 2021: a bullish market phase characterized by a level of volatility that remains moderate.
5. 17 November 2021 – 29 September 2022: a bearish market phase characterized by a level of volatility that remains moderately high.

4. Empirical results

This section examines the hedging effectiveness and asymmetric correlation of cryptocurrencies and cryptocurrency portfolios for

⁸ <https://www.nber.org/system/files/chapters/c2148/c2148.pdf>.

⁹ Dividing up the sample period based on volatility would result in roughly two market phases: one characterized by low volatility (28 March 2018–17 February 2020, average volatility 15.40) and the second characterized by high volatility (18 February 2020–29 September 2022, average volatility 26.07).

Table 2
Correlation table.

	STOXX	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	FSTOK300	FSTOKA	FSTOKE	USDT	GOLD
STOXX	1.000	0.215 ^{***}	0.239 ^{***}	0.043	0.048 [*]	0.035	0.045	0.043	0.038	-0.117	-0.038
BTC		1.000	0.746 ^{***}	0.278 ^{***}	0.239 ^{***}	0.190 ^{***}	0.278 ^{***}	0.278 ^{***}	0.231 ^{***}	0.026	0.085 ^{***}
ETH			1.000	0.282 ^{***}	0.255 ^{***}	0.211 ^{***}	0.283 ^{***}	0.283 ^{***}	0.254 ^{***}	0.050 [*]	0.068 ^{**}
FSTOK10				1.000	0.867 ^{***}	0.634 ^{**}	0.990 ^{***}	0.994 ^{***}	0.877 ^{***}	0.071 ^{**}	0.039
FSTOK40					1.000	0.649 ^{***}	0.884 ^{***}	0.884 ^{***}	0.978 ^{***}	0.060 ^{**}	0.042
FSTOK250						1.000	0.695 ^{***}	0.695 ^{***}	0.656 ^{***}	0.027	0.019
FSTOK300							1.000	0.994 ^{***}	0.886 ^{***}	0.070 ^{**}	0.038
FSTOKA								1.000	0.905 ^{***}	0.070 ^{**}	0.041
FSTOKE									1.000	0.059 ^{**}	0.040
USDT										1.000	0.087 ^{***}
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 ^{*}.

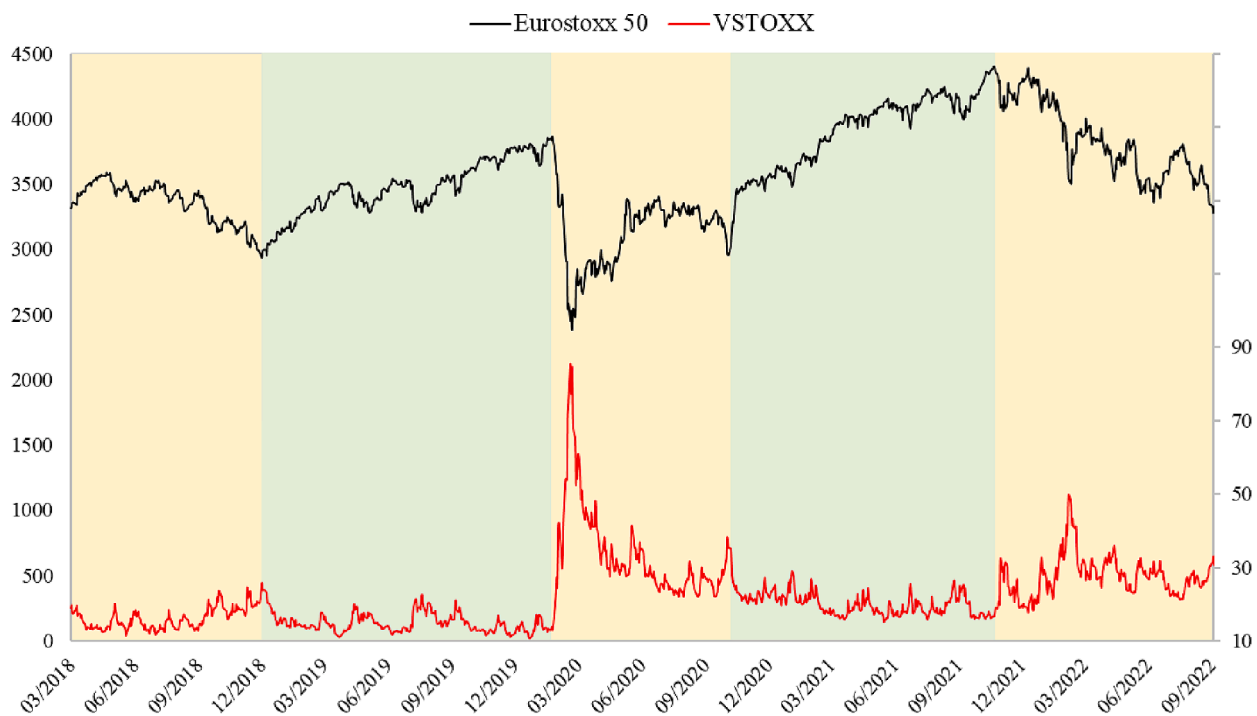


Fig. 1. Comparison between Eurostoxx 50 index and VSTOXX implied volatility index. Note: The Eurostoxx 50 index is shown in the values on the left, while VSTOXX implied volatility is shown in the values on the right. The shaded areas in the figure represent the different bullish and bearish market periods.

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 (BTC), Ethereum (ETH), Tether (USDT), FSTOK10, FSTOK40, FSTOK250, and GOLD is investigated in different market phases as defined in [Section 3.3](#). 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 five subsamples (t-stats are reported in parentheses). Several observations are in order. First, in four cases (Panels A, C, D, E), 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, E). 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 (0.228 and 0.170 for BTC and ETH, respectively) indicate that both Bitcoin and Ethereum do not act as safe haven assets for the STOXX. Similar results are obtained during the 2022 market downturn (Panel E), even if the magnitude of the coefficients is lower (0.123 and 0.091 for BTC and ETH, respectively).

Second, 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 and FSTOK250 returns are significantly related to STOXX returns during the period of COVID-19 market turbulence, 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, indicating a better diversification performance during market turbulences.

Third, the relationship between USDT and STOXX returns is negative and strongly significant during the 2022 market decline (Panel E), and negative but marginally significant in other two cases (Panels A, D). The result indicates that USDT can act as a safe haven for the European stock market during certain bearish market phases, suggesting the holding of stablecoin during a bearish market. The strong hedging performance of USDT in the last sample period (Panel E) is also motivated by the sharp hike in rates by the Federal Reserve following the surge in inflation. The results reported in the remaining panels suggest that European investors can

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

	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	USDT	GOLD
Panel A: 28 March 2018 – 27 December 2018							
STOXX (–1)	–0.059 (–0.813)	–0.056 (–0.764)	–0.056 (–0.765)	–0.054 (–0.730)	–0.065 (–0.880)	–0.063 (–0.861)	–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)	0.121* (1.683)	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)	–0.161** (–2.089)	–0.123 (–1.095)
X (–1)							
X (–2)							
X (–3)							
X (–4)							
Panel B: 27 December 2018 – 17 February 2020							
STOXX (–1)	–0.005 (–0.092)	–0.003 (–0.043)	–0.002 (–0.037)	–0.002 (–0.026)	–0.002 (–0.041)	–0.001 (–0.010)	–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)	–0.091 (–1.551)	–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)	–0.026 (–0.592)	–0.290*** (–3.957)
X (–1)							
X (–2)							
X (–3)							
X (–4)							
Panel C: 18 February 2020 – 30 October 2020							
STOXX (–1)	0.024 (0.354)	0.035 (0.510)	–0.095 (–1.192)	–0.159** (–1.997)	–0.113 (–1.438)	–0.060 (–0.580)	–0.015 (–0.207)
STOXX (–2)			0.122 (1.528)		0.124 (1.574)	0.175** (2.222)	0.144* (1.942)
STOXX (–3)						0.072 (0.706)	
STOXX (–4)						0.202* (1.698)	
X	0.228*** (6.489)	0.170*** (6.443)	0.070* (1.964)	0.095*** (2.846)	0.082** (2.401)	–0.420 (–0.866)	0.316** (2.254)
X (–1)			0.047 (1.286)	0.076** (2.448)	0.048 (1.355)	0.767*** (2.797)	
X (–2)			0.013 (0.396)	0.037 (1.212)	0.023 (0.715)	0.070 (0.178)	
X (–3)			0.113*** (3.412)	0.115*** (3.812)	0.111*** (3.535)	1.280** (2.387)	
X (–4)							

Linear ARDL models: short-run coefficient estimates.

	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	USDT	GOLD
Panel D: 1 November 2020 – 16 November 2021							
STOXX (–1)	–0.083 (–1.393)	–0.073 (–1.223)	–0.075 (–1.225)	–0.079 (–1.278)	–0.077 (–1.257)	–0.115* (–1.888)	–0.064 (–1.057)
STOXX (–2)							
STOXX (–3)							
STOXX (–4)							
X	0.037*** (3.117)	0.028*** (3.256)	–0.009 (–0.818)	–0.003 (–0.365)	–0.007 (–1.019)	–0.298* (–1.946)	–0.181*** (–2.603)
X (–1)						0.067 (0.432)	0.129* (1.835)
X (–2)						–0.226 (–1.476)	–0.064 (–1.057)
X (–3)						0.285* (1.850)	
X (–4)							
Panel E: 17 November 2021 – 29 September 2022							
STOXX (–1)	–0.105 (–1.560)	–0.125* (–1.904)	–0.075 (–1.057)	–0.030 (–0.430)	–0.037 (–0.555)	–0.085 (–1.354)	–0.044 (–0.676)
STOXX (–2)	–0.114* (–1.700)	–0.091 (–1.471)	–0.134* (–1.881)				–0.093 (–1.430)
STOXX (–3)							

(continued on next page)

Table 3 (continued)

Linear ARDL models: short-run coefficient estimates.							
	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	USDT	GOLD
STOXX (−4)							
X	0.123*** (5.079)	0.091*** (5.013)	0.027 (1.074)	−0.014 (−0.600)	−0.010 (−0.603)	−0.999*** (−5.871)	−0.441*** (−3.903)
X (−1)	0.066** (2.575)	0.072*** (3.759)	0.038 (1.512)				
X (−2)	0.009 (0.336)						
X (−3)	0.006 (0.257)						
X (−4)	−0.070*** (−2.881)						

Note: The table shows the estimated short-run coefficients for the linear ARDL model described in Eq. (1), where the dependent variable is the STOXX and the independent variable (X) is alternatively proxied by BTC, ETH, FSTOK10, FSTOK40, FSTOK250, USDT, and GOLD. The 1 %, 5 %, and 10 % significance levels are indicated by *, **, and ***, respectively. For a definition of the series, see Table 1.

benefit from holding stablecoins in terms of diversification or hedging during both bullish and bearish market periods.

Fourth, 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 during the 2022 market decline (Panel E), and positive during the COVID-19 market downturn (Panel C). Therefore, gold tends to behave as a hedge during bullish market periods and during the recent market downturn (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 was significantly positive during the bear market period 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. Unlike single cryptocurrencies and cryptocurrency portfolios, Tether is negatively related or unrelated to the European stock market in all market phases under investigation, thus acting as an effective diversifier and as a hedge during market declines.

Regarding the role of gold, in the financial literature it 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](#)) report 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 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.

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 consists of five different panels, according to the five 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 almost all the models.¹⁰ The CUSUM and CUSUMQ plots, not reported in order to save space but available upon request, suggest that the coefficients of the variables are relatively stable in all models. Finally, an F-test is performed for the joint significance of the coefficients of variables related to lagged levels. Cointegration 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 (II Bound) reported in Table 4. The obtained F-statistic for cointegration 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 five market phases. This result is in line with [Thampanya et al. \(2020\)](#), indicating 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

¹⁰ Given that the LM statistic for the relationship between STOXX and USDT reported in Table 4 (Panel C) is above the threshold of 9.48, we report in the corresponding column in Table 3 (Panel C) the results obtained using the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix.

Table 4
Linear ARDL models: diagnostic tests for the short run and bounds test for cointegration.

	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	USDT	GOLD
Panel A: 28 March 2018 – 27 December 2018							
LM test	2.608	2.600	2.447	2.395	2.773	2.602	2.368
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Stable	Stable	Stable	Stable	Stable	Stable	Stable
F-statistic	27.253	26.737	26.199	25.856	26.775	27.617	26.130
I0 Bound	3.620	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	4.160
Panel B: 27 December 2018 – 17 February 2020							
LM test	1.409	1.418	1.995	1.802	1.487	3.127	1.214
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Stable	Stable	Stable	Stable	Stable	Stable	Stable
F-statistic	58.695	58.004	57.949	58.712	59.187	58.136	66.352
I0 Bound	3.620	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	4.160
Panel C: 18 February 2020 – 30 October 2020							
LM test	1.271	1.485	1.707	3.551	7.137	12.369	1.443
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Rather	Rather	Rather	Rather	Rather	Rather	Rather
F-statistic	92.177	91.762	23.479	71.278	24.021	14.055	23.580
I0 Bound	3.620	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	4.160
Panel D: 1 November 2020 – 16 November 2021							
LM test	4.735	4.901	6.922	8.953	9.274	8.617	4.195
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Stable	Stable	Stable	Stable	Stable	Stable	Stable
F-statistic	112.744	133.391	106.107	105.714	106.377	112.822	103.33
I0 Bound	3.620	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	4.160
Panel E: 17 November 2021 – 29 September 2022							
LM test	2.915	1.251	1.591	3.402	2.229	2.610	3.520
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Rather	Rather	Stable	Stable	Stable	Stable	Stable
F-statistic	50.860	65.053	47.186	79.748	79.750	103.39	53.943
I0 Bound	3.620	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	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, USDT 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).

cryptocurrencies. More specifically, while the findings suggest long-term adjustments, in many cases a short-term relationship was not detected. 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. As a result, 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 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), the market downturn occurring during the COVID-19 outbreak (Panel C), and the 2022 market decline (Panel E). The results for the remaining subsamples (Panel B and Panel D, not reported in the paper for reasons of space, but available on request) do not show any asymmetric pattern, suggesting that positive and negative cryptocurrency

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

	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	USDT	GOLD
Panel A: 28 March 2018 – 27 December 2018							
STOXX (−1)	−0.052 (−0.718)	−0.068 (−0.937)	−0.056 (−0.762)	−0.054 (−0.722)	−0.068 (−0.913)	−0.062 (−0.851)	−0.055 (−0.771)
STOXX (−2)	0.126* (1.729)	0.127* (1.772)	0.120* (1.654)	0.132* (1.771)	0.121 (1.635)	0.118 (1.634)	
STOXX (−3)							
STOXX (−4)							
X+	0.041** (2.326)	−0.017 (−1.108)	0.005 (0.251)	−0.015 (−0.755)	−0.006 (−0.312)	−0.054 (−0.391)	−0.570*** (−3.030)
X+ (−1)				−0.009 (−0.510)			
X+ (−2)				0.038** (2.191)			
X+ (−3)							
X+ (−4)							
X−	−0.005 (−0.343)	0.041*** (2.858)	0.021 (1.100)	0.019 (1.269)	0.017* (1.937)	−0.248** (−2.050)	0.357* (1.777)
X− (−1)				0.023 (1.431)	0.024 (1.611)		
X− (−2)				−0.020 (−1.264)	−0.007 (−0.465)		
X− (−3)				−0.023 (−1.550)	−0.030** (−2.041)		
X− (−4)							
Panel C: 18 February 2020 – 30 October 2020							
STOXX (−1)	−0.034 (−0.497)	−0.027 (−0.387)	−0.023 (−0.284)	−0.052 (−0.641)	−0.031 (−0.384)	−0.039 (−0.490)	−0.009 (−0.118)
STOXX (−2)			0.139* (1.721)		0.116 (1.428)		0.149** (1.994)
STOXX (−3)							
STOXX (−4)							
X+	0.099 (1.569)	0.079 (1.556)	0.176** (2.343)	0.162** (2.210)	0.144* (1.779)	−1.632*** (−2.618)	0.521* (1.930)
X+ (−1)	0.101* (1.656)	0.104** (2.165)		−0.001 (−0.014)	−0.013 (−0.161)	0.154 (0.284)	
X+ (−2)				0.257*** (3.541)	0.205*** (2.612)	−0.790 (−1.444)	
X+ (−3)						2.133*** (4.010)	
X+ (−4)							
X−	0.323*** (6.437)	0.231*** (6.159)	0.028 (0.634)	0.051 (1.272)	0.048 (1.154)	0.659 (1.106)	0.159 (0.708)
X− (−1)			0.071 (1.601)	0.100*** (2.634)	0.075* (1.791)		
X− (−2)			−0.028 (−0.692)	−0.055 (−1.415)	−0.051 (−1.265)		
X− (−3)			0.138*** (3.425)	0.177*** (4.816)	0.164*** (4.211)		
X− (−4)			−0.064 (−1.534)	−0.070* (−1.772)	−0.067* (−1.724)		
Nonlinear ARDL model: short-run coefficient estimates.							
	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	USDT	GOLD
Panel E: 17 November 2021 – 29 September 2022							
STOXX (−1)	−0.104 (−1.546)	−0.102 (−1.536)	−0.070 (−1.001)	−0.025 (−0.357)	−0.035 (−0.520)	−0.082 (−1.301)	−0.051 (−0.759)
STOXX (−2)	−0.120* (−1.783)		−0.140** (−2.050)	−0.121* (−1.769)			−0.124* (−1.857)
STOXX (−3)							
STOXX (−4)							
X+	0.086 (1.696)	0.040 (1.055)	−0.015 (−0.307)	−0.048 (−0.965)	−0.006 (−0.248)	−1.291*** (−4.453)	−0.611*** (−2.937)
X+ (−1)	0.028 (0.546)	0.074* (1.962)	0.116** (2.539)	0.099** (2.085)			
X+ (−2)	0.111** (2.198)						
X+ (−3)							

(continued on next page)

Table 5 (continued)

Nonlinear ARDL model: short-run coefficient estimates.							
X+ (-4)							
X -	0.154*** (4.267)	0.125*** (4.371)	0.059 (1.601)	0.016** (0.456)	-0.015 (-0.537)	-0.625* (-1.809)	-0.336 (-1.648)
X - (-1)	0.086** (2.275)	0.067** (2.254)					0.005 (0.025)
X - (-2)	-0.049 (-1.285)	-0.059** (-2.192)					-0.381** (-2.005)
X - (-3)	-0.008 (-0.226)						
X - (-4)	-0.093*** (-2.718)						

Note: The table shows the estimated short-run coefficients for the NARDL model described in Eq. (6), where the dependent variable is the STOXX and the independent variable (X) is alternatively proxied by BTC, ETH, FSTOK10, FSTOK40, FSTOK250, USDT, and GOLD. The 1 %, 5 %, and 10 % significance levels are indicated by *, **, and ***, respectively. For a definition of the series, see Table 1.

and gold returns have no significantly 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 cointegration analysis. The null hypothesis of no short-run asymmetry for the bearish market period from March to December 2018 (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. Unlike GOLD, only negative returns on USDT show a negative short-term association with STOXX returns, indicating that decreases in USDT are associated with positive STOXX returns. The result suggests that USDT failed to act as a safe haven for STOXX during the 2018 market decline. However, the negative sign in the relationship still suggests diversification benefits for investors that combine a position in stablecoin with one in the European stock market. Finally, 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.

Table 6

Nonlinear ARDL models: diagnostic tests for the short run and bounds test for cointegration.

	BTC	ETH	FSTOK10	FSTOK40	FSTOK250	USDT	GOLD
Panel A: 28 March 2018 – 27 December 2018							
LM test	2.056	3.752	2.957	1.770	1.987	4.160	3.002
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Wald test χ^2	1.895	5.649	0.241	0.110	0.108	0.873	8.434
Probability	0.169	0.018	0.623	0.741	0.742	0.351	0.004
F-statistic	21.215	21.964	19.630	19.174	20.330	20.917	55.974
I0 Bound	3.100	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	3.870
Panel C: 27 December 2018 – 17 February 2020							
LM test	0.599	0.234	0.319	1.210	2.001	7.329	2.269
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Rather Stable	Rather Stable	Rather Stable	Rather Stable	Rather Stable	Rather Stable	Rather Stable
Wald test χ^2	1.259	0.326	0.059	2.265	1.240	0.429	0.790
Probability	0.263	0.568	0.808	0.132	0.265	0.513	0.375
F-statistic	66.025	64.383	17.999	45.100	16.877	47.542	17.861
I0 Bound	3.100	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	3.870
Panel E: 17 November 2021 – 29 September 2022							
LM test	1.903	2.992	4.425	1.618	2.187	2.456	0.746
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable	Stable
CUSUMQ	Rather Stable	Stable	Rather Stable	Rather Stable	Stable	Stable	Stable
Wald test χ^2	0.787	0.057	0.269	0.167	0.053	1.547	0.053
Probability	0.376	0.811	0.605	0.683	0.818	0.215	0.818
F-statistic	39.476	70.058	36.495	34.082	59.569	78.118	38.580
I0 Bound	3.100	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	3.870

Note: The table shows several tests for the NARDL model described in Eq. (6), where the independent variable is alternatively proxied by BTC, ETH, FSTOK10, FSTOK40, FSTOK250, USDT, 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).

The results for the COVID-19 outbreak, reported in Table 5, Panel C, deserve a more detailed discussion. Even if the Wald test reported in Table 6 fails to reject the symmetry hypothesis, the distinction between positive and negative returns is crucial to understand the properties of cryptocurrencies as a hedge for European stocks. By examining contemporaneous returns (X_+ and X_-), strong evidence supporting the existence of an asymmetric effect is found for BTC, ETH, and GOLD.¹¹ 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 0.323 and 0.231 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, even gold did not act 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. A negative and significant relationship is detected between positive USDT returns and STOXX returns, pointing to a very strong role of USDT as a safe haven for European stocks during the COVID outbreak. The safe haven role of USDT also holds during the 2022 market decline, a period characterized by the Russian invasion of Ukraine, soaring inflation, aggressive central bank moves, and failures and bankruptcies that affect many players in the crypto industry.¹² During the 2022 market decline (Panel E), a safe haven role, even if weaker in terms of magnitude, is also detected for gold. In particular, GOLD returns show a strong negative relationship with STOXX returns. The negative relationship supports the role of GOLD as a safe haven in times of uncertainty, which was missing during the 2020 market downturn. Several factors may have contributed to the different behaviour of GOLD during the COVID outbreak and the 2022 market decline. 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 probably forced to liquidate their holdings, including gold, in order to meet margin requirements and maintain their portfolio positions.¹³

The results for cryptocurrencies and cryptocurrency portfolios in Panel E are similar to the ones obtained during the 2020 market decline (Panel C). Negative BTC/ETH returns are positively and significantly associated to market returns. However, the magnitude of the relationship (equal to 0.154 and 0.125 for BTC and ETH, respectively) is lower compared to the one in Panel C. Returns of cryptocurrency portfolios during the 2022 bear market period are not significantly related to STOXX returns, revealing better properties than single cryptocurrencies for diversification purposes.

Table 6 reports diagnostic tests in the short run and the Bounds test method, adopted to investigate the relationship between variables over the long run. In all models, estimated coefficients are relatively stable and the LM test indicates no autocorrelation in the error term. Table 6 reports the bounds test for cointegration. In all the periods under investigation, the F-statistic is above the threshold level of 3.870 (I1 Bound), indicating that positive and negative returns of BTC, ETH, USDT, GOLD and the three cryptocurrency portfolios have significant long-term relationships with STOXX.

To sum up, among the crypto assets only USDT prove to be a safe haven asset for STOXX in two out of the three bearish market phases, given the negative short-term relationship between positive returns on USDT and STOXX returns. On the other hand, 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. Unlike individual cryptocurrencies, 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 10 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. Additional empirical results

In this section, we investigate whether the results obtained for the Eurostoxx 50 index, which is the leading measure of the European stock market, can differ by country. Starting from the COVID-19 outbreak, the decoupling of the economic conditions observed

¹¹ The asymmetric effect is confirmed by a Wald test performed on the contemporaneous return coefficients, available upon request.

¹² Our dataset includes failures and bankruptcies that affect TerraUSD/Luna in May 2022, Celsius Network in June 2022, and Voyager Digital in July 2022, while we discard events regarding FTX and BlockFi in November 2022. However, it is worth noting that the main results for the relationship between the European stock market and cryptocurrencies obtained in the last market phase (Panel E) would not have changed even if the dataset had been extended to the end of November. Thus, to be consistent with the turning point method described in Section 3.3, we set the end of the dataset at the Eurostoxx 50 period minimum that occurred on 29 September 2022.

¹³ <https://www.spglobal.com/marketintelligence/en/news-insights/research/collateral-margin-calls-currency-and-fear-covid-19-impact-on-gold>.

throughout Europe may have affected the relationship between each country's stock market index and cryptocurrencies. In the following analysis, we consider a subset of countries represented in the Eurostoxx 50 index. Since its launch in 1998, the Eurostoxx 50 index has represented the performance of the Eurozone's 50 super-sector leading companies. Among the 19 Eurozone member countries (as of 2022), only 12 of these countries' stock markets are large and liquid enough to be eligible for the Eurostoxx 50 index.¹⁴ These are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. Actually, five countries (France, Germany, the Netherlands, Spain and Italy) represent more than 90 % of Eurostoxx 50 market capitalization.¹⁵ As a result, our analysis will be focused on these five markets.

The correlation coefficients between stock market indices for France (CAC), Germany (DAX), the Netherlands (AEX), Spain (IBEX) and Italy (MIB), crypto assets, and gold are represented in Fig. 2 in terms of daily returns. Several observations can be made. First, the correlation between the five indices and STOXX are all above 0.90, with CAC and DAX being the ones with the highest correlation. Second, the returns for the five stock market indices are positively correlated with BTC and ETH (around 0.20) and show a lower correlation with cryptocurrency portfolios. Third, unlike the other indices, MIB is characterized by a correlation with cryptocurrency portfolios close to zero. The low correlation of the Italian market with cryptocurrency portfolios can be related to its composition. In particular, the Italian market is focused on energy and financial stocks, while cryptocurrencies could be associated with the technological sector. Finally, all the stock market indices are negatively related to USDT in terms of daily returns.

In order to further investigate the relationship between country market indices and cryptocurrencies, we perform the Autoregressive Distributed Lag (ARDL) and the non-linear ARDL models presented in Section 3.1 and 3.2 replacing STOXX with the return series of the five market indices (DAX, CAC, AEX, IBEX, MIB). For the sake of comparison, we perform the analysis for the relation between stock market indices, Bitcoin, Ethereum, FSTOK10, FSTOK40, FSTOK250, USDT and GOLD in the different market phases as defined in Section 3.3. In order to save space, we report a synthetic description of the results for the short-run in the five subsamples in Table 7, while the complete results are available on request.

In each Panel, the results for STOXX are reported in the first line for the sake of comparison. In general, the results obtained for the five indices are very similar to those obtained for STOXX, especially during bullish market phases (see Panel B and D of Table 7 where we report the main results of the linear ARDL model). In particular, in Panel B, showing the results for the bullish period between 27 December 2018 and 17 February 2020, all the indices are negatively and significantly related to GOLD returns, while no relationships were detected between stock market indices and the remaining variables. As regards Panel D, showing the results for the bullish market period between 1 November 2020 and 16 November 2021, most of the stock market indices are positively related to BTC and ETH, and negatively related to USDT and GOLD. A few exceptions are represented by AEX and MIB that are not related to GOLD and USDT, respectively, and by IBEX, which shows only a weak negative association with GOLD returns, with no significant relationship with the crypto assets under investigation. No relation with cryptocurrency portfolios is detected for any of the market indices.

For the bearish market periods (Panels A, C, and E), we rely more on the results obtained using the NARDL model, which provides deeper insight into the relationship between variables. During the bearish market period in 2018 (Panel A), the most important result is that GOLD acted as a safe haven for all the stock market indices under investigation (i.e., positive GOLD returns are negatively and significantly associated with stock market returns). Moreover, most of the indices are weakly associated with positive returns of BTC, and ETH, with the only exceptions of IBEX and MIB, which are related only to positive returns in one of the two major cryptocurrencies (ETH for IBEX and BTC for MIB). AEX is the only index which is negatively related to negative ETH returns, while DAX is the only index that presents a weak, positive relationship with a cryptocurrency portfolio (FSTOK250). Also in this market phase, coefficients for the contemporaneous relationship between stock market and cryptocurrency returns are low. Finally, we detected a negative relationship between negative USDT returns and market returns for DAX, IBEX, and MIB.

The results obtained for the bearish market period that occurred during the COVID outbreak in 2020 (Panel C) are similar to those obtained for STOXX. In particular, a strong positive short-term association is detected between negative BTC/ETH returns on the one hand and stock market returns on the other for all the indices under investigation, indicating the risk of large joint losses. Moreover, USDT acted as a safe haven asset for all the stock market indices, whereas GOLD failed to do so. Finally, DAX and CAC show more similarities with STOXX being positively related to FSTOK10 and FSTOK40 positive returns. On the other hand, AEX is found to be positively related to negative returns in FSTOK40 and FSTOK250, suggesting the possibility of joint tail risk, even if the coefficients of the relationship are lower than in the case of BTC and ETH. In addition, the results for the 2022 market decline, reported in Panel E, are similar to those obtained for STOXX. The most important result is that both USDT and GOLD acted as a safe haven for all the stock market indices during the 2022 market downturn. Moreover, a strong positive relationship is detected between negative BTC/ETH returns on the one hand and stock market returns on the other for all the indices under investigation. Finally, among the five stock market indices, only AEX and IBEX are associated (positively) with a cryptocurrency portfolio (FSTOK10).

To sum up, the analysis of the relationship between major stock market indices in the Euro area and crypto-asset reveals that the implication obtained for the Eurostoxx 50 holds with few exceptions also for the five major European markets (Germany, France, the Netherlands, Spain, and Italy). However, it is interesting to note that some stock market indices, such as the Italian and Spanish ones, are characterized by a weaker relationship with cryptocurrencies and cryptocurrency portfolios in certain periods. On the other hand, the stock market index for the Netherlands revealed a higher relationship with cryptocurrency portfolios during the 2020 and 2022 market declines. Although we leave an in-depth analysis of the relationship between individual stock market indices and

¹⁴ https://www.stoxx.com/document/Research/Expert-speak-articles/INVESTING_IN_EUROPE_USING_THE_EURO_STOXX_50_AN_AUSTRALIAN_PERSPECTIVE.pdf.

¹⁵ <https://www.stoxx.com/document/Bookmarks/CurrentFactsheets/SX5GT.pdf>.

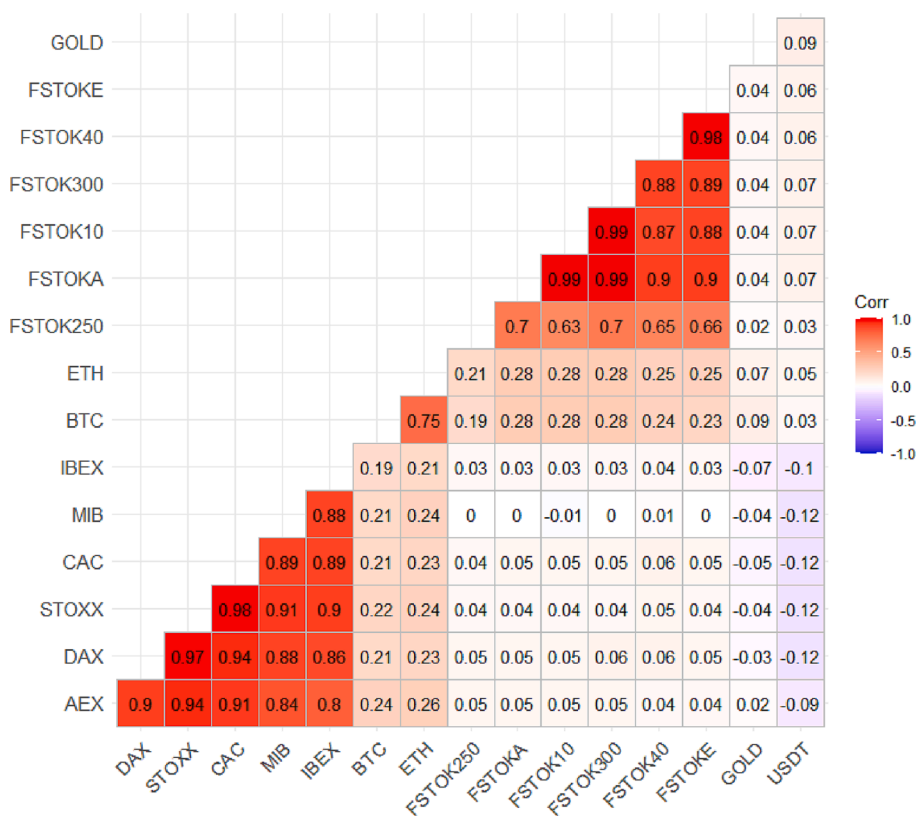


Fig. 2. Correlations between major market indices in the Euro area, cryptocurrencies, and gold.

cryptocurrencies to future work, we suspect that these differences are at least in part related to the sectoral composition of national indices. While in the Italian and the Spanish markets, traditional sectors such as oil, energy and financial services are prevalent, the first sector in terms of weight in the AEX index is technology, the behaviour of which can be more closely compared to that of cryptocurrencies.

6. Conclusions

This paper has investigated hedging effectiveness and asymmetric correlations of two cryptocurrencies (Bitcoin, Ethereum), a stablecoin (Tether), cryptocurrency portfolios, and gold for the European stock market. From the investor’s 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 has examined safe haven properties of two cryptocurrencies (Bitcoin and Ethereum), a stablecoin (Tether) and cryptocurrency portfolios and contrasted them with gold as a benchmark. As a reference for European stocks, the Eurostoxx 50 index was used, covering 50 of the largest and most liquid stocks (blue-chip) in eight Eurozone countries. Following Thampanya et al. (2020), the study applies 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 have been obtained.

First, among the crypto assets under investigation (Bitcoin, Ethereum, Tether and the six cryptocurrency portfolios), only Tether proved to be an overall safe haven for the Eurostoxx 50 during the period 2018–2022. In particular, Tether positive returns are found to be negatively related to STOXX in two out of the three bearish market phases (2020 and 2022) considered in our sample, indicating that European investors can benefit from stablecoins in order to hedge or diversify their portfolios. On the other hand, Bitcoin and Ethereum are found to be the most closely correlated to the stock market, showing a significant relationship in four out of five market phases. Second, the NARDL model used to disentangle positive and negative returns casts 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 has been 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

Table 7

Brief description of the results for the relationship between Euro area stock market indices and cryptocurrencies.

	BTC	ETH	Cryptocurrencies portfolios	USDT	GOLD
Panel A: 28 March 2018 – 27 December 2018					
STOXX	positively related to BTC ⁺ , weak	positively related to ETH ⁻		negatively related to USDT ⁻	safe haven effect
DAX	positively related to BTC ⁺ , weak	positively related to ETH ⁻	positively related to FSTOK250 ⁻	negatively related to USDT ⁻	safe haven effect
CAC	positively related to BTC ⁺ , weak	positively related to ETH ⁻			safe haven effect
AEX	positively related to BTC ⁺ , weak	posit. (negat.) related to ETH ⁻ (ETH ⁺)			safe haven effect
IBEX		positively related to ETH ⁻ , weak		negatively related to USDT ⁻	safe haven effect
MIB	positively related to BTC ⁺ , weak			negatively related to USDT ⁻	safe haven effect
Panel B: 27 December 2018 – 17 February 2020					
All the stock market indices are negatively and significantly related to GOLD returns					
Panel C: 18 February 2020 – 30 October 2020					
STOXX	positively related to BTC ⁻	positively related to ETH ⁻	positively related to FSTOK10 ⁺ and FSTOK40 ⁺	safe haven effect	positively related to GOLD ⁺
DAX	positively related to BTC ⁻	positively related to ETH ⁻	positively related to FSTOK10 ⁺ and FSTOK40 ⁺	safe haven effect	positively related to GOLD ⁺
CAC	positively related to BTC ⁻	positively related to ETH ⁻	positively related to FSTOK10 ⁺ and FSTOK40 ⁺	safe haven effect	
AEX	positively related	positively related	positively related to FSTOK40 ⁻ and FSTOK250 ⁻	safe haven effect, weak	positively related to GOLD ⁺
IBEX	positively related to BTC ⁻	positively related to ETH ⁻		safe haven effect	
MIB	positively related to BTC ⁻	positively related to ETH ⁻		safe haven effect	
Panel D: 1 November 2020 – 16 November 2021					
STOXX	positively related	positively related		negatively related	negatively related
DAX	positively related	positively related		negatively related	negatively related
CAC	positively related	positively related		negatively related	negatively related
AEX	positively related	positively related		negatively related	
IBEX					negatively related, weak
MIB	positively related	positively related			negatively related, weak
Panel E: 17 November 2021 – 29 September 2022					
STOXX	positively related to BTC ⁻	positively related to ETH ⁻		safe haven effect	safe haven effect
DAX	positively related to BTC ⁻	positively related to ETH ⁻		safe haven effect	safe haven effect
CAC	positively related to BTC ⁻	positively related to ETH ⁻		safe haven effect	safe haven effect
AEX	positively related to BTC ⁻	positively related to ETH ⁻	positively related to FSTOK10 ⁻	safe haven effect	safe haven effect
IBEX	positively related to BTC ⁻	positively related to ETH ⁻	Positively related to FSTOK10 ⁻	safe haven effect	safe haven effect
MIB	positively related to BTC ⁻	positively related to ETH ⁻		safe haven effect	safe haven effect

Note: The table briefly describes the results for the relationship between Euro area stock market indices and cryptocurrencies. The results are based on an estimation of the linear and nonlinear ARDL models described in Eqs. (1) and (6). The dependent variable is alternatively proxied by DAX, CAC, AEX, IBEX, and MIB. The independent variable (X) is alternatively proxied by BTC, ETH, FSTOK10, FSTOK40, FSTOK250, USDT, and GOLD. We indicate as “safe haven effect” a negative relationship between positive crypto asset or gold returns and the stock market index returns. Subscript + (-) indicates the positive (negative) innovation in the independent variables when commenting on the results of the NARDL model. We use the term “weak” to describe a relationship significant at the 10 % level.

cryptocurrency portfolios may be 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 attract 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, showing a better risk-return profile compared to portfolios made up of a large number of minor cryptocurrencies. Fifth, the results reveal that gold acted as a safe haven during the

bear markets in 2018 and 2022 but not during the COVID-19 related downturn in 2020, raising the need for alternative safe haven investments. Finally, the results obtained for the Eurostoxx 50 index remain valid when investigating five major markets of the Euro area such as Germany, France, the Netherlands, Spain and Italy. Minor differences have been found for Spain and Italy since these markets are less closely correlated to cryptocurrencies, suggesting higher diversification opportunities.

We believe that the results of the paper will be of interest to investors, financial intermediaries, and regulators. Investors could exploit the results for asset allocation purposes or to improve forecasting models. The findings indicate that adding a single cryptocurrency to a stock portfolio does not provide effective hedging during market downturns and can increase the risk of short-term joint losses. However, adding a mix of cryptocurrencies to a stock portfolio might lead to some diversification benefits. In particular, given the speculative characteristics of cryptocurrencies and their enormous volatility, any investor exposure to these assets should be viewed 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. On the other hand, including a stablecoin in a portfolio made up of European stocks may provide hedge or diversification during bearish market phases. The emergence of a positive effect from cryptocurrencies in terms of diversification benefits can be favoured not only by specific market conditions but also by developing adequate innovation in the underlying technologies and projects. Investment product managers could rely on these results to develop tradeable assets that replicate an investment in multiple cryptocurrencies to provide investors with an additional tool to diversify their holdings. Regarding optimal portfolio allocation between the different asset classes, the solution needs to be established by investors and fund managers and must reflect the individual investor's risk profile, taking into account that cryptocurrencies are extremely volatile.

In light of the results of the present study, cryptocurrencies can be viewed as alternative investment solutions in periods characterized by bullish market conditions and low volatility. On the other hand, given their tremendous volatility, the high exposure to tail risk, and the increasing short-term correlation with the traditional assets, cryptocurrencies can carry high risks, especially for small investors with insufficient financial knowledge. In fact, from the investor's point of view, it can be difficult to operate in the jungle of new crypto projects (currently more than 20,000 cryptocurrencies are traded), often characterized by high levels of complexity and highly innovative and technological content. The increasing market complexity, related to the fact that different cryptocurrencies rely on different technologies and characteristics to achieve specific possibilities for potential users ([Antonakakis et al., 2019](#)), along with the high degree of uncertainty about their intrinsic value ([Borgards and Czudaj, 2020](#)) makes it a challenging task for an investor to assess the value of a cryptocurrency. Therefore, the crypto market characteristics can stimulate the entry of specialized companies that can select projects and create portfolios to be subsequently traded in traditional markets or exploiting traditional channels (e.g., exchange-traded funds).

The focus of regulators and policymakers should now be devoted to the research of appropriate solutions to protect investors intending to enter these markets, even with the support of traditional intermediaries and commonly used investment channels (e.g., ETF). First, a greater awareness of risks is essential for investors approaching the cryptocurrency market. At the same time, regulators and policymakers should move towards tighter regulation for companies that offer cryptocurrency investment services to the retail public, including increasing transparency requirements and assessing cybersecurity systems before issuing a permit or license to cryptocurrency exchanges.¹⁶ A better assessment of these risks can help prevent the recurrence of situations such as high-risk business deals, potentially fraudulent activities, and in the worst case the failure of major exchanges and institutions. In particular, in a market characterized by the lack of a central regulatory institution with the function of lender of last resort, intermediaries are exposed to sudden and extreme financial phenomena such as bank runs and credit crunches, and the collapse of an institution can have cascading effects on the cryptocurrency and traditional markets.

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 in traditional financial markets 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.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

¹⁶ According to [Grobys et al. \(2022\)](#), a major issue for the cryptocurrency market is represented by hacking incidents, since in the period 2011–2021, approximately 1.7 million units of Bitcoin are estimated to have been stolen due to criminal activity with losses exceeding USD 700 million.

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References

- Adeiran, I.A., Yinusa, O.D., Lakhani, K.H., 2021. Where lies the silver lining when uncertainty hang dark clouds over the global financial markets? *Resour. Policy* 70, 101932. <https://doi.org/10.1016/j.resourpol.2020.101932>.
- Ahluwalia, S., Mahto, R.V., Guerrero, M., 2020. Blockchain technology and startup financing: A transaction cost economics perspective. *Technol. Forecast. Soc. Chang.* 151, 119854 <https://doi.org/10.1016/j.techfore.2019.119854>.
- Akyildirim, E., Corbet, S., Lucey, B., Sensoy, A., Yarovaya, L., 2020. The relationship between implied volatility and cryptocurrency returns. *Financ. Res. Lett.* 33, 101212 <https://doi.org/10.1016/j.frl.2019.06.010>.
- Antonakakis, N., Chatziantoniou, I., Gabauer, D., 2019. Cryptocurrency market contagion: Market uncertainty, market complexity, and dynamic portfolios. *J. Int. Finan. Markets. Inst. Money* 61, 37–51. <https://doi.org/10.1016/j.intfin.2019.02.003>.
- Balcilar, M., Bouri, E., Gupta, R., Roubaud, D., 2017. Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Econ. Model.* 64, 74–81. <https://doi.org/10.1016/j.econmod.2017.03.019>.
- Baur, D.G., Hoang, L.T., 2021. A crypto safe haven against Bitcoin. *Financ. Res. Lett.* 38, 101431 <https://doi.org/10.1016/j.frl.2020.101431>.
- Beckmann, J., Berger, T., Czudaj, R., 2015. Does gold act as a hedge or a safe haven for stocks? A smooth transition approach. *Econ. Modell., Special Issue on Current Challenges on Macroeconomic Analysis and International Finance Modelling* 48, 16–24. <https://doi.org/10.1016/j.econmod.2014.10.044>.
- Bekiros, S., Boubaker, S., Nguyen, D.K., Uddin, G.S., 2017. Black swan events and safe havens: The role of gold in globally integrated emerging markets. *J. Int. Money Finan., Global Econ.: Future Finan. Macro Challenges* 73, 317–334. <https://doi.org/10.1016/j.jimonfin.2017.02.010>.
- Bhimani, A., Hausken, K., Arif, S., 2022. Do national development factors affect cryptocurrency adoption? *Technol. Forecast. Soc. Chang.* 181, 121739 <https://doi.org/10.1016/j.techfore.2022.121739>.
- Bicchetti, D., Maystre, N., 2013. The synchronized and long-lasting structural change on commodity markets: Evidence from high frequency data. *Algorithmic Finance* 2, 233–239. <https://doi.org/10.3233/AF-13028>.
- Bilgin, M.H., Gozgor, G., Lau, C.K.M., Sheng, X., 2018. The effects of uncertainty measures on the price of gold. *Int. Rev. Financ. Anal.* 58, 1–7. <https://doi.org/10.1016/j.irfa.2018.03.009>.
- Borgards, O., Czudaj, R.L., 2020. The prevalence of price overreactions in the cryptocurrency market. *J. Int. Finan. Markets. Inst. Money* 65, 101194. <https://doi.org/10.1016/j.intfin.2020.101194>.
- Borri, N., 2019. Conditional tail-risk in cryptocurrency markets. *J. Empir. Financ.* 50, 1–19. <https://doi.org/10.1016/j.jempfin.2018.11.002>.
- Bouri, E., Gupta, R., Tiwari, A.K., Roubaud, D., 2017a. Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Financ. Res. Lett.* 23, 87–95. <https://doi.org/10.1016/j.frl.2017.02.009>.
- Bouri, E., Jalkh, N., Molnár, P., Roubaud, D., 2017b. Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven? *Appl. Econ.* 49, 5063–5073. <https://doi.org/10.1080/00036846.2017.1299102>.
- Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L.L., 2017c. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Financ. Res. Lett.* 20, 192–198. <https://doi.org/10.1016/j.frl.2016.09.025>.
- Bouri, E., Shahzad, S.J.H., Roubaud, D., Kristoufek, L., Lucey, B., 2020. Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. *Q. Rev. Econ. Finance* 77, 156–164. <https://doi.org/10.1016/j.qref.2020.03.004>.
- Brauneis, A., Mestel, R., 2019. Cryptocurrency-portfolios in a mean-variance framework. *Financ. Res. Lett.* 28, 259–264. <https://doi.org/10.1016/j.frl.2018.05.008>.
- Brière, M., Oosterlinck, K., Szafarz, A., 2015. Virtual currency, tangible return: Portfolio diversification with bitcoin. *J. Asset Manag.* 16, 365–373. <https://doi.org/10.1057/jam.2015.5>.
- Chang, V., Baudier, P., Zhang, H., Xu, Q., Zhang, J., Arami, M., 2020. How Blockchain can impact financial services—The overview, challenges and recommendations from expert interviewees. *Technological forecasting and social change*, 158, 120166. <https://doi.org/10.1016/j.techfore.2020.120166>.
- Charfeddine, L., Benlagha, N., Maouchi, Y., 2020. Investigating the dynamic relationship between cryptocurrencies and conventional assets: Implications for financial investors. *Econ. Model.* 85, 198–217. <https://doi.org/10.1016/j.econmod.2019.05.016>.
- Ciner, C., Gurdgiev, C., Lucey, B.M., 2013. Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. *Int. Rev. Financ. Anal.* 29, 202–211. <https://doi.org/10.1016/j.irfa.2012.12.001>.
- Conlon, T., McGee, R., 2020. Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. *Financ. Res. Lett.* 35, 101607 <https://doi.org/10.1016/j.frl.2020.101607>.
- Dickey, D.A., Fuller, W.A., 1979. Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *J. Am. Stat. Assoc.* 74, 427–431. <https://doi.org/10.2307/2286348>.
- Elyasiani, E., Gambarelli, L., Muzzioli, S., 2021. The skewness index: uncovering the relationship with volatility and market returns. *Appl. Econ.* 53, 3619–3635. <https://doi.org/10.1080/00036846.2021.1884837>.
- Elyasiani, E., Muzzioli, S., 2022. The power of deterministic option-implied trees in pricing European options. *Appl. Econ.* 54 (22), 2596–2609. <https://doi.org/10.1080/00036846.2021.1998330>.
- Elyasiani, E., Gambarelli, L., Muzzioli, S., 2020. Moment risk premia and the cross-section of stock returns in the European stock market. *J. Bank. Financ.* 111, 105732 <https://doi.org/10.1016/j.jbankfin.2019.105732>.
- Figà-Talamanca, G., Focardi, S., Patacca, M., 2021. Common dynamic factors for cryptocurrencies and multiple pair-trading statistical arbitrages. *Decisions Econ. Finan.* 44 (2), 863–882. <https://doi.org/10.1007/s10203-021-00318-x>.
- Figà-Talamanca, G., Focardi, S., Patacca, M., 2021. Regime switches and commonalities of the cryptocurrencies asset class. *North Am. J. Econ. Finan.* 57, 101425. <https://doi.org/10.1016/j.najef.2021.101425>.
- Flavin, T.J., Morley, C.E., Panopoulou, E., 2014. Identifying safe haven assets for equity investors through an analysis of the stability of shock transmission. *J. Int. Finan. Markets. Inst. Money* 33, 137–154. <https://doi.org/10.1016/j.intfin.2014.08.001>.
- Frijns, B., Verschoor, W.F.C., Zwinkels, R.C.J., 2017. Excess stock return comovements and the role of investor sentiment. *J. Int. Finan. Markets. Inst. Money* 49, 74–87. <https://doi.org/10.1016/j.intfin.2017.02.005>.
- Grobys, K., Junttila, J., Kolari, J.W., Sapkota, N., 2021. On the stability of stablecoins. *J. Empir. Financ.* 64, 207–223. <https://doi.org/10.1016/j.jempfin.2021.09.002>.
- Grobys, K., Duftinema, J., Sapkota, N., Kolari, J.W., 2022. What's the expected loss when Bitcoin is under cyberattack? A fractal process analysis. *J. Int. Finan. Markets. Inst. Money* 77, 101534.
- Guesmi, K., Saadi, S., Abid, I., Ftiti, Z., 2019. Portfolio diversification with virtual currency: Evidence from bitcoin. *Int. Rev. Financ. Anal.* 63, 431–437. <https://doi.org/10.1016/j.irfa.2018.03.004>.
- Hung, N.T., 2021. Bitcoin and CEE stock markets: fresh evidence from using the DECO-GARCH model and quantile on quantile regression. *Eur. J. Manag. Bus. Econ.* 30 (2), 261–280. <https://doi.org/10.1108/EJMBE-06-2020-0169>.
- Huynh, T.L.D., Burggraf, T., Nasir, M.A., 2020a. Financialisation of natural resources & instability caused by risk transfer in commodity markets. *Resour. Policy* 66, 101620. <https://doi.org/10.1016/j.resourpol.2020.101620>.

- Huynh, T.L.D., Hille, E., Nasir, M.A., 2020b. Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds and cryptocurrencies. *Technol. Forecast. Soc. Chang.* 159, 120188 <https://doi.org/10.1016/j.techfore.2020.120188>.
- 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. *J. Int. Financ. Markets. Inst. Money* 56, 255–280. <https://doi.org/10.1016/j.intfin.2018.01.002>.
- Kajtazi, A., Moro, A., 2019. The role of bitcoin in well diversified portfolios: A comparative global study. *Int. Rev. Financ. Anal.* 61, 143–157. <https://doi.org/10.1016/j.irfa.2018.10.003>.
- Kapetanios, G., Shin, Y., Snell, A., 2003. Testing for a unit root in the nonlinear STAR framework. *J. Econ.* 112, 359–379. [https://doi.org/10.1016/S0304-4076\(02\)00202-6](https://doi.org/10.1016/S0304-4076(02)00202-6).
- Kapetanios, G., Shin, Y., Snell, A., 2006. Testing for Cointegration in Nonlinear Smooth Transition Error Correction Models. *Economet. Theor.* 22, 279–303. <https://doi.org/10.1017/S026646660600129>.
- Kumar, A., Iqbal, N., Mitra, S.K., Kristoufek, L., Bouri, E., 2022. Connectedness among major cryptocurrencies in standard times and during the COVID-19 outbreak. *J. Int. Financ. Markets. Inst. Money* 77, 101523. <https://doi.org/10.1016/j.intfin.2022.101523>.
- Le, T.-L., Abakah, E.J.A., Tiwari, A.K., 2021. Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution. *Technol. Forecast. Soc. Chang.* 162, 120382 <https://doi.org/10.1016/j.techfore.2020.120382>.
- Li, J.-P., Naqvi, B., Rizvi, S.K.A., Chang, H.-L., 2021. Bitcoin: The biggest financial innovation of fourth industrial revolution and a portfolio's efficiency booster. *Technol. Forecast. Soc. Chang.* 162, 120383 <https://doi.org/10.1016/j.techfore.2020.120383>.
- Liu, W., 2019. Portfolio diversification across cryptocurrencies. *Financ. Res. Lett.* 29, 200–205. <https://doi.org/10.1016/j.frl.2018.07.010>.
- Ma, Y., Ahmad, F., Liu, M., Wang, Z., 2020. Portfolio optimization in the era of digital financialization using cryptocurrencies. *Technol. Forecast. Soc. Chang.* 161, 120265 <https://doi.org/10.1016/j.techfore.2020.120265>.
- Ngo, N.S., Nguyen, H.T.M., 2021. A Safe-haven Property of Cryptocurrencies: Evidence in Vietnam Stock Market During Pandemic Crisis. *J. Asian Financ., Econ. Bus.* 8 (12), 465–471. <https://doi.org/10.13106/jafeb.2021.vol8.no12.0465>.
- Nyberg, H., 2013. Predicting bear and bull stock markets with dynamic binary time series models. *J. Bank. Financ.* 37 (9), 3351–3363. <https://doi.org/10.1016/j.jbankfin.2013.05.008>.
- Pesaran, M.H., Shin, Y., 1999. An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis. In: Strom, S. (Ed.), *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*. Cambridge University Press, Cambridge.
- Pesaran, M.H., Shin, Y., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. *J. Appl. Economet.* 16, 289–326. <https://doi.org/10.1002/jae.616>.
- Petukhina, A., Trimborn, S., Härdle, W.K., Elendner, H., 2021. Investing with Cryptocurrencies – evaluating their potential for portfolio allocation strategies. *Quantitative Finance*. <https://doi.org/10.1080/14697688.2021.1880023>.
- Platanakis, E., Urquhart, A., 2019. Portfolio management with cryptocurrencies: The role of estimation risk. *Econ. Lett.* 177, 76–80. <https://doi.org/10.1016/j.econlet.2019.01.019>.
- Raddant, M., Kenett, D.Y., 2021. Interconnectedness in the global financial market. *J. Int. Money Financ.* 110, 102280 <https://doi.org/10.1016/j.jimonfin.2020.102280>.
- Rao, A., Gupta, M., Sharma, G.D., Mahendru, M., Agrawal, A., 2022. Revisiting the financial market interdependence during COVID-19 times: a study of green bonds, cryptocurrency, commodities and other financial markets. *Int. J. Manag. Financ.* 18, 725–755. <https://doi.org/10.1108/IJMF-04-2022-0165>.
- Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L., Lucey, B., 2019. Is Bitcoin a better safe-haven investment than gold and commodities? *Int. Rev. Financ. Anal.* 63, 322–330. <https://doi.org/10.1016/j.irfa.2019.01.002>.
- Shin, Y., Yu, B., Greenwood-Nimmo, M., 2014. Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework. In: Sickles, R.C., Horrace, W.C. (Eds.), *Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications*. Springer, New York, NY, pp. 281–314. https://doi.org/10.1007/978-1-4899-8008-3_9.
- Su, C.-W., Qin, M., Tao, R., Shao, X.-F., Albu, L.L., Umar, M., 2020a. Can Bitcoin hedge the risks of geopolitical events? *Technol. Forecast. Soc. Chang.* 159, 120182 <https://doi.org/10.1016/j.techfore.2020.120182>.
- Su, C.-W., Qin, M., Tao, R., Umar, M., 2020b. Financial implications of fourth industrial revolution: Can bitcoin improve prospects of energy investment? *Technol. Forecast. Soc. Chang.* 158, 120178 <https://doi.org/10.1016/j.techfore.2020.120178>.
- Symitsi, E., Chalvatzis, K.J., 2018. Return, volatility and shock spillovers of Bitcoin with energy and technology companies. *Econ. Lett.* 170, 127–130. <https://doi.org/10.1016/j.econlet.2018.06.012>.
- Symitsi, E., Chalvatzis, K.J., 2019. The economic value of Bitcoin: A portfolio analysis of currencies, gold, oil and stocks. *Res. Int. Bus. Financ.* 48, 97–110. <https://doi.org/10.1016/j.ribaf.2018.12.001>.
- Thampanya, N., Nasir, M.A., Huynh, T.L.D., 2020. Asymmetric correlation and hedging effectiveness of gold & cryptocurrencies: From pre-industrial to the 4th industrial revolution. *Technol. Forecast. Soc. Chang.* 159, 120195 <https://doi.org/10.1016/j.techfore.2020.120195>.
- Ullah, S., Zaefarian, G., Ullah, F., 2020. How to use instrumental variables in addressing endogeneity? A step-by-step procedure for non-specialists. *Ind. Mark. Manag.* 96 <https://doi.org/10.1016/j.indmarman.2020.03.006>.
- Umar, M., Rizvi, S.K.A., Naqvi, B., 2021a. Dance with the devil? The nexus of fourth industrial revolution, technological financial products and volatility spillovers in global financial system. *Technol. Forecast. Soc. Chang.* 163, 120450 <https://doi.org/10.1016/j.techfore.2020.120450>.
- Umar, M., Su, C.-W., Rizvi, S.K.A., Shao, X.-F., 2021b. Bitcoin: A safe haven asset and a winner amid political and economic uncertainties in the US? *Technol. Forecast. Soc. Chang.* 167, 120680 <https://doi.org/10.1016/j.techfore.2021.120680>.
- Umar, Z., Trabelsi, N., Alqahtani, F., 2021c. Connectedness between cryptocurrency and technology sectors: International evidence. *Int. Rev. Econ. Financ.* 71, 910–922. <https://doi.org/10.1016/j.iref.2020.10.021>.
- Wang, H., Wang, X., Yin, S., Ji, H., 2022. The asymmetric contagion effect between stock market and cryptocurrency market. *Financ. Res. Lett.* 46, 102345 <https://doi.org/10.1016/j.frl.2021.102345>.
- Wu, S., Tong, M., Yang, Z., Derballi, A., 2019. Does gold or Bitcoin hedge economic policy uncertainty? *Financ. Res. Lett.* 31, 171–178. <https://doi.org/10.1016/j.frl.2019.04.001>.
- Yi, E., Ahn, K., Choi, M.Y., 2022. Cryptocurrency: Not far from equilibrium. *Technol. Forecast. Soc. Chang.* 177, 121424 <https://doi.org/10.1016/j.techfore.2021.121424>.
- Yousaf, I., Ali, S., 2020. Discovering interlinkages between major cryptocurrencies using high-frequency data: new evidence from COVID-19 pandemic. *Financial Innovation* 6, 45. <https://doi.org/10.1186/s40854-020-00213-1>.