

MODELING THE DEPENDENCE STRUCTURE BETWEEN BITCOIN, GOLD, AND EQUITY MARKETS IN TIMES OF CRISIS: A COPULA-BASED PERSPECTIVE

Hana Belhadj¹, Nadia Belkhir^{2*}, Salah Ben Hamad³

Received 22.09.2025.

| Sent to review 15.10.2025. | Accepted 18.02.2026.

Original article



¹ Faculty of Economics and Management of Sfax, University of Sfax, Tunisia

² Imam Mohammad Ibn Saud Islamic University (IMSIU), Saudi Arabia

³ University of Tunis El-Manar, Tunisia

*Corresponding Author:

Nadia Belkhir

Email:

nabelkhir@imamu.edu.sa

JEL Classification:

G11, G15, C32, C58, E44, F65

Doi: 10.2478/eoik-2026-0018

UDK: 339.13.053.2:336.744

ABSTRACT

This paper investigates whether Bitcoin serves as a safe haven and a diversification tool for both developed and emerging stock markets during the COVID-19 crisis, in comparison with gold. The analysis covers daily data from June 18, 2012, to May 25, 2020, across a representative set of developed (S&P500, FTSE100, DAX, CAC40, Nikkei225, Ibex35) and emerging (Shanghai, Nifty50, Ibovespa, MOEX) equity markets, providing a comprehensive view of asset interactions in different financial environments. Methodologically, we employ a two-step approach: an EGARCH model to estimate time-varying volatility, followed by a copula-based framework to capture nonlinear and asymmetric dependence structures. This combination allows for a nuanced assessment of asset behavior under both tranquil and crisis conditions. The results show that Bitcoin maintains weak dependence on developed equity markets during the COVID-19 period but fails to display consistent safe-haven characteristics under extreme stress. Gold, by contrast, continues to act as a reliable hedge, confirming its traditional role in protecting portfolios against market downturns. Overall, these findings suggest that while Bitcoin may provide diversification benefits under normal circumstances, it cannot yet replace gold as a robust safe-haven asset. For portfolio managers, this highlights the importance of gold in risk management, while underscoring Bitcoin's evolving yet still uncertain role in global financial markets.

Keywords: *Bitcoin, Gold, Safe haven, COVID-19, Portfolio diversification*

1. INTRODUCTION

The COVID-19 pandemic has reignited the debate on the search for safe-haven assets capable of protecting investors during periods of extreme market turmoil. Traditionally, gold has been regarded as the most reliable safe haven (Baur & Lucey, 2010), but the emergence of Bitcoin has raised the question of whether digital assets could represent a credible alternative to traditional hedging instruments. The literature provides mixed evidence: while some studies suggest that Bitcoin, with its low correlation to equity markets, may serve as a portfolio diversifier (Bouri et al., 2017; Corbet et al., 2018), others highlight its excessive volatility and inability to consistently act as a safe haven during global crises (Cocco et al., 2022; Zhao, 2022). This ongoing debate points to a clear research gap, particularly regarding the comparative perfor-

mance of Bitcoin and gold across developed and emerging markets during systemic shocks. This study contributes to the growing literature on safe-haven and diversification assets by offering a multi-dimensional comparison of Bitcoin and gold across both developed and emerging stock markets. Unlike most existing works, which either focus on a single market type or examine only the COVID-19 episode, our framework combines an EGARCH model for volatility with copula methods to capture nonlinear dependence structures across three distinct market regimes: the sovereign debt crisis, the tranquil period, and the COVID-19 crisis. This dual perspective, contrasting Bitcoin with gold while also distinguishing between developed and emerging markets, provides novel evidence on the heterogeneous nature of safe-haven and diversification properties. The findings offer new insights into both academic debate and practical portfolio allocation, highlighting the context in which Bitcoin may complement, rather than replace, the traditional role of Gold.

The remainder of this paper is organized as follows: Section 2 reviews the existing literature, Section 3 outlines the methodology, Section 4 describes the data and provides descriptive statistics, Section 5 presents and discusses the empirical results, Section 6 offers a general discussion, and Section 7 concludes with implications and directions for future research.

2. LITERATURE REVIEW

The traditional role of gold as a safe haven during periods of financial turmoil is well established. Empirical studies, such as (Baur and Lucey, 2010) (Areal et al., 2015), (Belkhir, 2025) and (Belhadj et Ben Hamad 2025), highlight its ability to protect portfolios against extreme market shocks. Henriksen (2018) also emphasizes that commodities in general can serve as effective diversifiers by reducing downside risk in both developed and emerging markets. However, since the global financial crisis (Vankov & Lukarev, 2025), the reliability of gold as a safe haven has been called into question. Prolonged low interest rates and the increasing financialization of gold have raised doubts about its effectiveness (Shahzad et al., 2019). In parallel, Bitcoin has emerged as an alternative asset, often perceived as a response to the fragility of the traditional financial system, and has been proposed as a potential safe haven during periods of systemic stress. Early empirical research, however, provides mixed evidence. Some studies employing traditional methods such as GARCH-type models, linear regressions, and correlation analyses report weak correlations between Bitcoin and equity markets, suggesting potential diversification benefits (Bouri et al., 2017). Corbet et al. (2018) further show that Bitcoin appears largely disconnected from macroeconomic and financial variables, reinforcing its perception as a non-correlated asset. The COVID-19 pandemic has reignited this debate. As a unique global shock, it provides an unprecedented context to reassess the hedging and diversification properties of financial assets. (Cocco et al., 2022) find that Bitcoin exhibited weak correlations with major equity indices during the pandemic, which tends to confirm its potential role as a safe haven. Nevertheless, Zhao (2022) points out that while Bitcoin may act as a safe haven during localized crises, it fails to sustain this role in the face of a systemic global shock. In contrast, gold has consistently demonstrated its resilience during the pandemic, as shown by Belhadj et al. (2021), who highlight that gold served as a safe haven during COVID-19, unlike Bitcoin, which did not offer similar protection. Similarly, Nedved and Kristoufek (2023) highlight that, unlike Bitcoin, whose dynamics are closely linked to stock market movements, gold retains its role as a safe haven, demonstrating its ability to protect portfolios against the volatility of digital assets during times of crisis. In the same vein, Widjaja et al. (2024) confirm that gold remains a strong safe haven during market turmoil. In contrast, cryptocurrencies exhibit only a weak and unstable hedging capacity against stock market volatility. Consistently, Tarchella et al. (2024) provide further evidence that gold continues to offer robust safe-haven and diversification ben-

efits for G7 equity markets, while cryptocurrencies fail to deliver comparable protective effects, particularly during the post-COVID-19 period. Taken together, the literature suggests that while gold continues to act as a reliable safe haven in periods of severe market stress, Bitcoin's role remains uncertain and highly context dependent. This highlights the need to further investigate the comparative safe haven and diversification properties of gold and Bitcoin, particularly with respect to developed and emerging equity markets during the COVID-19 crisis.

3. METHODOLOGY

3.1. MODELING OF THE MARGINAL DISTRIBUTION

To model the conditional volatility of financial returns, we employ an EGARCH (1,1) model, initially introduced by (Nelson, 1991), which extends the traditional GARCH framework proposed by (Bollerslev, 1986). EGARCH models are particularly suited for capturing key stylized facts of financial time series, such as volatility clustering, time-varying variance, and asymmetric responses to shocks, where negative news tends to increase volatility more than positive news of the same magnitude. Although the GARCH(1,1) model remains one of the most widely used tools for modeling volatility in financial data (Bollerslev et al., 1992), the EGARCH specification offers additional flexibility, especially in the presence of leverage effects. Furthermore, the model produces standardized residuals that are approximately i.i.d., which is a necessary condition for the subsequent copula-based dependence modeling. Importantly, Aloui et al. (2013) show that the empirical results of copula models are generally robust to the specific GARCH-type specification employed in the first stage, particularly when copula parameters are estimated using the Maximum Canonical Likelihood (MCL) method. This approach is adopted in our study.

The conditional variance in the EGARCH model is expressed in logarithmic form as follows:

$$\log \sigma_t^2 = w + \beta \log \sigma_{t-1}^2 + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} \quad (1)$$

With w is the constant, α : The ARCH effect, γ : The asymmetry coefficient, if $\gamma \neq 0$ means that the impact of news is asymmetrical, β : The GARCH effect

This model allows us to capture the volatility dynamics and assess the impact of past returns (both in terms of magnitude and sign) on future volatility. The EGARCH specification, with its logarithmic formulation, ensures that the conditional variance remains positive and accommodates the leverage effect, where negative shocks tend to increase volatility more than positive shocks of the same magnitude.

3.2. COPULA THEORY

Since traditional Pearson correlation fails to capture non-linear relationships and tail dependence between financial assets, we adopt a copula-based approach to model the dependence structure between asset returns. Originally introduced by Sklar (1959) and later developed for financial applications (Cherubini et al., 2004), copula models have become widely used to investigate complex and asymmetric dependence structures across markets, particularly during periods of financial stress. A major advantage of copulas is their ability to model joint distributions without assuming normality is a critical feature given that financial returns often exhibit skewness, kurtosis, and heavy tails. Copulas allow for the separate modeling of marginal distributions and the dependence structure, providing a flexible and powerful framework for analyzing financial comovements. In the context of this study, the copula approach is particularly appropriate, as it enables us to detect changes in the dependence between Bitcoin, gold, and

stock market indices, especially during extreme market events such as the COVID-19 crisis. Traditional linear correlation measures may underestimate the true risk of co-movement during such turbulent periods.

Previous studies, such as (Jondeau and Rockinger, 2006) and (Patton, 2006), have demonstrated the efficacy of copulas in modeling conditional and asymmetric dependencies in financial markets. (Jondeau and Rockinger, 2006) applied a copula-GARCH framework to European stock markets, while Patton showed how copulas can capture asymmetric dependence in exchange rates. Building on this literature, we use copula models to investigate dynamic and potentially asymmetric relationships between the assets in our sample. Following Baur and Lucey (2010), we distinguish between two key concepts: hedge and safe-haven assets. An asset is considered a hedge if it is uncorrelated or negatively correlated with stock market returns on average, providing diversification benefits under normal market conditions. In contrast, a safe-haven asset is uncorrelated or negatively correlated with stock markets during periods of extreme market stress or downturns. Within the copula framework, these properties are captured through dependent parameters. Weak or negative dependence in the central part of the joint distribution indicates a hedge property, while low or negative lower-tail dependence reflects a safe-haven behavior. This distinction allows us to formally evaluate whether Bitcoin and gold act as hedging or safe-haven assets across different market regimes.

Mathematically, a bivariate copula used in this study is written as:

$$F(X_1, X_2) = C(F_1(X_1), F_2(X_2)) \quad (2)$$

Where, C : The copula function; X_1, X_2 : Random variables; F_1, F_2 : The marginal distributions of X_1, X_2 respectively.

In this study, we utilize both elliptical and Archimedean copulas to model the dependence between two variables. These copulas represent the most commonly used forms in financial applications and are frequently employed in empirical studies. Elliptical copulas, such as the Gaussian and Student's t copulas, are used to model symmetric dependence between the variables. They are particularly useful when the dependence is uniform in both tails of the distribution. Archimedean copulas, such as the Gumbel, Clayton, and Frank copulas, allow for asymmetric dependence. The Gumbel copula captures dependence in the upper (right) tail, while the Clayton copula focuses on dependence in the lower (left) tail. Unlike Gumbel and Clayton copulas, the Frank copula is unique in its ability to model both positive and negative dependence simultaneously, making it useful for capturing more complex dependencies. These copulas offer flexibility in modelling different forms of dependence, allowing for a more accurate representation of the relationship between the variables in the study. Although the copulas employed are static, the analysis distinguishes three distinct sub-periods representing different market regimes, which allows us to capture structural changes in dependence over time. Moreover, the marginal distributions are modelled using EGARCH specifications, which account for the conditional volatility dynamics before estimating the copulas.

A- GAUSSIAN COPULA

The Gaussian copula, belonging to the elliptical family, is the most widely used copula in finance. It is directly derived from the multivariate normal distribution and is particularly suited to modeling symmetric dependence between variables.

The Gaussian copula is defined as:

$$c(u, v) = \Phi_\rho(\Phi^{-1}(u), \Phi^{-1}(v)) \quad (3)$$

Where Φ_ρ denotes the cumulative distribution function (CDF) of the bivariate standard normal distribution with linear correlation coefficient ρ and $\Phi^{-1}(\cdot)$ is the inverse of the univariate standard normal CDF.

The corresponding density function is given by:

$$c(u, v) = \frac{1}{\sqrt{1-\rho^2}} \exp\left(-\frac{\rho^2 - 2\rho z_u z_v}{2(1-\rho^2)}\right) \quad (4)$$

with $z_u = \Phi^{-1}(u)$ and $z_v = \Phi^{-1}(v)$.

The parameter $\rho \in [-1, 1]$ measures the strength and direction of the linear dependence between the two variables. When $\rho = 0$, the copula reduces to the product copula, implying independence.

B- STUDENT-T

Analogous to the Gaussian copula, the Student-t copula is directly derived from the multivariate Student-t distribution. The dependence structure of the Student-t copula can be defined as follows:

$$C^t(u, v) = t_{\rho, v}(t_v^{-1}(u), t_v^{-1}(v)) \quad (5)$$

$$c(u, v) = \frac{1}{2\pi\sqrt{1-\rho^2}} \left(1 + \frac{t_v^{-1}(u)^2 - 2\rho t_v^{-1}(u)t_v^{-1}(v) + t_v^{-1}(v)^2}{v(1-\rho^2)}\right)^{-\frac{v+2}{2}} \quad (6)$$

With $t_{\rho, v}$: is the cumulative distribution function of the bivariate Student-t with correlation parameter ρ and degrees of freedom v .

C- CLAYTON COPULA

The Clayton copula is an Archimedean copula that is used to model only positive dependencies and to capture the asymmetry between tail dependencies. Specifically, it is particularly effective for modelling situations where there is a stronger dependency in the lower tail (i.e., when both variables are low) than in the upper tail (i.e., when both variables are high). This characteristic makes it suitable for modelling certain financial assets, particularly those with strong co-movements during adverse market conditions. The Clayton copula is defined as follows:

$$C(u, v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta} \quad (7)$$

$u, v \in [0, 1]$, θ Shows the parameter of the copula that belongs to the interval $[0, \infty]$. If $\theta \rightarrow 0$, the two variables are independent. Whereas if $\theta \rightarrow \infty$, the two variables have a perfect positive dependence.

D- GUMBEL

Gumbel's copula is valuable in the Archimedean family, particularly useful because it captures non-linear dependencies and asymmetric tail dependencies. Similar to the Clayton copula, the Gumbel copula models only positive dependencies, but it is particularly effective in modelling extreme co-movements in the upper tail, where both variables exhibit high values. This makes it especially useful for analysing situations where joint extreme positive events (high values) are of concern. It is defined as follows:

$$C(u, v) = \exp\left\{-\left[(-\ln u)^{1/\theta} + (-\ln v)^{1/\theta}\right]^\theta\right\} \quad (8)$$

With $u, v \in [0,1]$. θ : Parameter of Gumbel's copula, $1 \leq \theta \leq \infty$, which expresses the degree of dependence, if $\theta = 1$ the two variables are independent. Whereas, if $\theta \rightarrow \infty$ the degree of dependence is close to perfect dependence

E- FRANK

Unlike other Archimedean copulas, which are typically asymmetric, Frank's copula is symmetric and captures the full range of dependencies, including both lower and upper tail dependencies. Frank's copula is particularly useful when modeling assets that exhibit moderate dependencies, as it captures both positive and negative associations between variables, with a focus on low tail dependence.

Frank's copula is defined as follows:

$$C(u, v) = -\frac{1}{\theta} \ln \left(1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{(e^{-\theta} - 1)} \right) \quad (9)$$

With θ the parameter of the copula.

3. 2. 1. ESTIMATION OF COPULA PARAMETERS

There are several methods for estimating copula parameters, each with distinct advantages depending on the data and model. The method of moments provides a simple approach by matching sample and theoretical moments, though it is generally less efficient. The Maximum Likelihood (ML) method is the most efficient and widely applied technique when the likelihood function is tractable. The Inference Functions for Margins (IFM) approach estimates the marginal distributions first and then the copula parameters, which is useful when margins are complex. Finally, the Canonical Maximum Likelihood (CML) method estimates all parameters jointly, ensuring consistency and efficiency when the marginal distributions are modeled simultaneously with the copula. In our application, we have chosen the CML method for parameter estimation because it provides robust and efficient estimates when dealing with non-standard marginal distributions and interdependent data.

$$\hat{a} = \underset{a}{\operatorname{argmax}} \sum_{t=1}^T \ln c(\hat{u}_1^T, \dots, \hat{u}_1^T; a) \quad (10)$$

3. 2. 2. SIGNIFICANCE TESTING OF COPULA PARAMETERS

To assess the statistical significance of the estimated copula parameters, we used a bootstrap-based approach to compute an approximate p-value. This procedure involves randomly resampling the data with replacement ($n = 1000$ iterations), re-estimating the copula parameter for each bootstrap sample, and calculating a Z-statistic based on the standard deviation of the estimates. The p-value is then derived assuming a normal distribution of the Z-statistic. A p-value below 0.10 indicates that the parameter is statistically significant at the 90% confidence level.

3. 2. 3. SELECTION MODEL

Several methods exist for selecting the best copula model, including distance measures, chi-square tests, and information criteria such as AIC and BIC. In this study, we rely on AIC and BIC, which are widely applied in copula selection (Hussain et al., 2018). A lower value of these criteria indicates a better fit, meaning the chosen copula more closely reflects the empirical data. The AIC criterion can be defined as follows:

$$AIC = -2 \log(\text{likelihood}) + 2k \quad (11)$$

With k is the Number of parameters used in the model.

The BIC criterion can be defined as follows:

$$BIC = -2\log(\text{likelihood}) + k\log(n) \quad (12)$$

Where n is the number of data points and k is the number of parameters used in the model.

This approach allows us to compare different copula models based on their ability to fit the data, while penalizing overly complex models (i.e., models with too many parameters). The AIC and BIC criteria are particularly useful when selecting a model that minimizes prediction error while avoiding overfitting.

4. DATA AND STATISTICS DESCRIPTIVE

To analyze the dependence structure between Bitcoin, gold, and major international stock markets, we use daily closing prices covering the period from June 18, 2012, to May 25, 2020, resulting in 2071 observations per series. The data were obtained from DataStream International, and Investing.com asset prices are expressed in U.S. dollars (USD) to ensure international comparability and to eliminate currency conversion effects. Following standard practice in the safe-haven literature, we use price indices rather than total return indices. The developed markets in our sample include the DAX (Germany), CAC40 (France), IBEX35 (Spain), FTSE100 (UK), NIKKEI225 (Japan), and S&P500 (USA). The emerging markets are represented by the IBOVESPA (Brazil), NIFTY50 (India), MOEX (Russia), and the Shanghai Composite Index (China). A previous study by (Belkhir and al. 2025), employed most of these indices in their empirical analysis, which further supports the relevance and robustness of our market selection. These indices were selected based on their representativeness, market size, and relevance in previous financial contagion and safe-haven studies.

Daily logarithmic returns are computed as:

$$\text{Ln}(P_t / P_{t-1}) \quad (13)$$

With: P_t , P_{t-1} denote the daily closing prices at times t and $t-1$, respectively.

Weekends and market holidays were excluded to align all series on common trading days across markets. Following BNP Paribas Research and previous studies, the full sample is divided into three distinct and non-overlapping subperiods: the Sovereign Debt Crisis (June 18, 2012 – June 28, 2013), the Tranquil Period (July 1, 2013 – December 31, 2019), and the COVID-19 Crisis (January 1, 2020 – May 25, 2020). The last subperiod encompasses the initial phase of the COVID-19 pandemic, marked by financial shock and market turbulence.

Table 1 reports the descriptive statistics, including the mean, maximum, and minimum returns, standard deviation, skewness, kurtosis, and the Jarque-Bera normality test for the daily returns of Bitcoin, gold, and major developed and emerging stock market indices over the full sample period. These statistics were computed using EViews software. All assets exhibit positive average daily returns, with Bitcoin yielding the highest mean return of 0.34%, followed by the Nikkei225 (Japan) with an average return of 0.042%. In terms of volatility, as measured by standard deviation, Bitcoin is the most volatile asset (5.29%), while the FTSE100 (UK) is the least volatile, with a standard deviation of 0.96%. To assess the distributional properties of the return series, we use the Jarque-Bera test along with skewness and kurtosis measures. Under the null hypothesis of normality, skewness should be zero, and kurtosis should be equal to three. The skewness coefficient captures the asymmetry of the return distribution: negative values indicate a left-skewed distribution, while positive values suggest a right-skewed distribution. The kurtosis coefficient indicates the degree of peakedness or tail thickness; values greater than three suggest a leptokurtic distribution (fat tails), while values less than three imply a platykurtic

tic distribution. The results indicate that most return series deviate from normality, as evidenced by non-zero skewness, excess kurtosis, and high Jarque-Bera statistics. These findings justify the use of models that can handle non-normal features, such as GARCH-type models and copulas, in the subsequent empirical analysis.

Table 1. Descriptive statistics of the variables for the entire period

	Mean	Max	Min	Std	Skewness	Kurtosis	Jarque Bera	Prob
Bitcoin	0.34%	0.38	-0.48	5.29%	-0.62	13.84	101281	0.000
Gold	0.01%	1.21	-1.20	4%	0.29	803.62	55312962	0.000
Dax	0.029%	0.10	-0.13	1.20%	-0.76	15.38	13442	0.000
Cac40	0.18%	0.08	-0.13	1.19%	-1.03	15.24	13.299	0.000
Ftse100	0.0043%	0.086	-0.11	0.96%	-1.05	19.98	25283	0.000
Ibex35	0.0009%	0.075	-0.15	1.32%	-1.34	18.80	22193	0.000
Nikkei225	0.042%	0.07	-0.08	1.30%	-0.29	8.19	2358	0.000
S&P500	0.038%	0.08	-0.12	1.03%	-1	28.63	57041	0.000
Ibovespa	0.014%	0.13	-0.15	1.55%	-1.06	19.39	23592	0.000
Nifty50	0.027%	0.08	-0.13	1.05%	-1.45	26.50	48415	0.000
Shanghai Index	0.0096	0.05	-0.08	1.34%	-1.12	10.85	5766	0.000
Moex	0.033%	0.074	-0.11	1.15%	-0.86	14.43	11548	0.000

Source: Authors Preparations

5. RESULTS

5.1. RESULTS FOR MARGINAL DISTRIBUTION MODELS

We begin by identifying the most appropriate marginal distribution model for each return series over the sample period. Specifically, we estimate the parameters of the conditional mean equation using an ARMA process, and the conditional variance equation using an EGARCH (1,1) specification. For each asset, several ARMA–EGARCH models are estimated without any exogenous regressors. To avoid overfitting and ensure parsimony, the optimal specification is selected based on the Akaike Information Criterion (AIC). Tables 2, 3, and 4 in the Appendix report the ARMA–EGARCH models selected for each series across the three market regimes: the Sovereign Debt Crisis, the stable period, and the COVID-19 period.

The ARMA–EGARCH estimates (reported in Appendix Tables 5–7) confirm the presence of volatility clustering and persistence across all markets, as both ARCH (α) and GARCH (β) coefficients are significant. Moreover, the asymmetric parameter (γ) indicates leverage effects, with negative shocks generally exerting stronger impacts on volatility. These results validate the suitability of the EGARCH framework for capturing time-varying volatility dynamics.

5.2. COPULA

Tables 8 to 13 report the parameter estimates for Archimedean (Frank, Clayton, Gumbel) and elliptical (Gaussian, Student-t) copulas, estimated with MATLAB. Model selection relies on AIC and BIC, where lower values indicate a better fit.

Table 8, covering the sovereign debt crisis, shows extremely weak dependence between Bitcoin and both developed and emerging stock indices. For most pairs, the Gumbel copula reaches its lower bound (parameter = 1), while the Frank and Clayton copulas produce parameters close to zero, all indicating near independence. The elliptical copulas (Gaussian and Bitcoin-t) similarly yield very low or slightly negative values, confirming the absence of linear or tail dependence.

Across models, the lowest AIC and BIC values are generally associated with the Gumbel specification, reinforcing that minimal-dependence models best fit the data. However, none of the estimated coefficients are statistically significant, implying that these patterns should be interpreted with caution. Overall, Bitcoin appears largely decoupled from equity markets during the sovereign debt crisis, which is consistent with its potential role as a diversification instrument in periods of market stress, though this interpretation lacks statistical confirmation.

Table 8. Estimation of the parameters of the different copulas between Bitcoin and stock market indices during the sovereign crisis

	Archimedean copulas			Elliptical copulas	
	Frank	Clayton	Gumbel	Normal	Student
BTC –Dax	-0.603	1.45 ^E -6	1	-0.09	-0.90
AIC	3.207	2.000	0.000	2.180	4.180
BIC	8.115	6.907	4.907	7.087	13.995
BTC-Cac40	-0.237	1.45 ^E -6	1	-0.034	-0.034
AIC	2.475	2.000	0.000	2.068	4.068
BIC	7.382	6.907	4.907	6.975	13.885
BTC-Ibex35	-0.375	1.45 ^E -6	1	-0.073	-0.073
AIC	2.751	2.000	0.000	2.146	4.146
BIC	7.659	6.907	4.907	7.053	13.961
BTC-Ftse100	-0.470	1.45 ^E -6	1	-0.070	-0.070
AIC	2.940	2.000	2.000	2.140	4.140
BIC	7.848	6.907	4.907	7.047	13.955
BTC-S&P500	-0.203	0.027	1	-0.023	-0.023
AIC	2.407	1.946	0.000	2.046	4.046
BIC	7.315	6.853	4.907	6.953	13.861
BTC-Nikkei225	0.51	0.10	1.03	0.08	0.08
AIC	0.963	1.783	-0.078	1.840	3.840
BIC	5.870	6.690	4.829	6.747	13.655
BTC-Ibovespa	-0.275	0.029	1	-0.048	-0.048
AIC	2.550	1.940	0.000	2.096	4.096
BIC	7.458	6.848	4.907	7.003	13.911
BTC-Nifty50	-0.126	0.043	1	-0.026	-0.024
AIC	2.253	1.913	0.000	2.052	4.048
BIC	7.161	6.821	4.907	6.959	13.863
BTC-Shanghai	0.22	0.08	1.01	0.042	0.040
AIC	1.548	1.820	0.000	1.916	3.920
BIC	6.455	6.728	4.873	6.823	13.735
BTC-Moex	-0.25	1.45 ^E -6	1	-0.056	-0.056
AIC	2.503	2.000	0.000	2.112	4.112
BIC	7.410	6.907	4.907	7.019	13.927

Source: Authors Preparations

Table 9 presents the copula parameter estimates between Bitcoin and stock indices during the non-crisis period. Using both Archimedean (Frank, Clayton, Gumbel) and elliptical (Gaussian, Student-t) copulas, with model selection based on AIC and BIC, the results indicate weak dependence overall, though slightly higher than in crisis periods. Frank and Clayton copulas show modestly positive values with some developed indices, such as the DAX and FTSE100,

but these remain close to zero. Elliptical copulas also yield very low estimates, confirming the absence of significant linear dependence. Since none of the coefficients are statistically significant, the observed relationships should be interpreted with caution. Overall, Bitcoin exhibits largely independent behavior even in tranquil markets, suggesting its potential as a diversification asset, although this relationship remains weak and context dependent.

Table 9. Estimation of the parameters of the different copulas between Bitcoin and stock market indices during the non-crisis period

	Archimedean copulas			Elliptical copulas	
	Frank	Clayton	Gumbel	Normal	Student
BTC –Dax	0.084	0.017	1	0.014	0.014
AIC	1.830	1.965	0.000	1.972	3.972
BIC	6.738	6.873	4.907	6.879	13.787
BTC-Cac40	0.012	0.0163	1	0.004	0.004
AIC	1.975	1.967	0.000	1.992	3.992
BIC	6.883	6.875	4.907	6.899	13.807
BTC-Ibex35	0.098	0.039	1	0.017	0.017
AIC	1.802	1.921	0.000	1.966	3.966
BIC	6.710	6.828	4.907	6.873	13.781
BTC-Ftse100	-0.064	0.007	1	-0.01	-0.01
AIC	2.129	1.984	0.000	2.020	4.020
BIC	7.037	6.892	4.907	6.927	13.835
BTC-S&P500	-0.042	0.01	1	-0.005	-0.006
AIC	2.084	1.977	0.000	2.01	4.012
BIC	6.992	6.885	4.907	6.917	13.827
BTC-Nikkei225	-0.20	1.45 ^E -6	1	-0.032	-0.033
AIC	2.403	2	0.000	2.064	4.066
BIC	7.311	6.907	4.907	6.971	13.881
BTC-Ibovespa	0.040	0.02	1.003	0.0149	0.0145
AIC	1.919	1.958	-0.006	1.970	3.971
BIC	6.827	6.866	4.901	6.878	13.786
BTC-Nifty50	-0.242	1.45 ^E -6	1	-0.024	-0.024
AIC	2.485	2.000	0.000	2.048	4.048
BIC	7.393	6.907	4.901	6.955	13.863
BTC-Shanghai	-0.030	0.020	1.010	-0.002	-0.0038
AIC	2.070	1.959	0.000	2.004	4.007
BIC	6.978	6.866	4.886	6.912	13.823
BTC-Moex	0.134	0.044	1	0.021	0.021
AIC	1.731	1.910	0.000	1.958	3.958
BIC	6.639	6.818	4.907	6.865	13.733

Source: Authors Preparations

Table 10 presents the estimated copula parameters between Bitcoin and stock indices during the COVID-19 crisis. Among the models tested, the Gumbel copula, which records the lowest AIC and BIC values, provides the best overall fit and reveals evidence of upper-tail dependence. The results show that most copulas are statistically significant for the CAC40 (at the 10% level), and for the FTSE100 and MOEX (at the 5% level), while for the DAX, only the Gaussian copula displays statistical significance. To avoid redundancy and emphasize the economic

interpretation, the analysis focuses on the Gumbel copula, which captures asymmetric dependence in extreme market conditions. The coefficients, mostly positive and significant, indicate that during the crisis, Bitcoin moved in tandem with major European markets, notably the CAC40, FTSE100, and MOEX, suggesting a temporary loss of its safe-haven property. Compared to the pre-crisis period, the magnitude of the coefficients increases, although some remain statistically insignificant, reflecting a temporary strengthening of linkages between Bitcoin and certain developed markets, particularly in Europe. From an economic perspective, these findings suggest that during the pandemic, Bitcoin behaved more like a risky asset integrated into global financial markets rather than a safe haven, illustrating its vulnerability to global shocks and the convergence of its behavior with traditional assets under stress.

Table 10. Estimation of the parameters of the different copulas between Bitcoin and stock market indices during the COVID-19 crisis

	Archimedean copulas			Elliptical copulas	
	Frank	Clayton	Gumbel	Normal	Student
BTC –Dax	1.135	0.343	1.173	0.256*	0.169
AIC	-0.270	1.313	-0.347	1.488	3.662
BIC	4.637	6.220	4.560	6.390	13.477
BTC-Cac40	1.125*	0.355*	1.12*	0.225*	0.225*
AIC	-0.251	1.289	-0.243	1.550	3.550
BIC	4.656	6.196	4.664	6.457	13.365
BTC-Ibex35	0.58	0.262	1.11	0.186	0.09
AIC	0.839	1.475	-0.222	1.628	3.820
BIC	5.747	6.383	4.685	6.535	13.635
BTC-Ftse100	1.44**	0.32**	1.19**	0.25**	0.22**
AIC	-0.891	1.350	-0.381	1.500	3.560
BIC	4.015	6.258	4.526	6.407	13.375
BTC-S&P500	0.009	0.105	1.05	0.091	0.027
AIC	1.652	1.753	-0.130	2.214	3.900
BIC	6.560	6.666	4.777	7.121	13.715
BTC-Nikkei225	0.55	0.168	1.10	0.125	0.09
AIC	0.882	1.663	-0.211	1.750	3.818
BIC	5.789	6.571	4.696	6.057	13.633
BTC-Ibovespa	0.51	0.25	1.06	0.147	0.098
AIC	0.972	1.495	-0.138	1.706	3.804
BIC	5.880	6.403	4.769	6.613	13.619
BTC-Nifty50	-0.3	0.11	1	0.022	-0.02
AIC	2.617	1.763	0.000	1.956	4.040
BIC	7.525	6.671	4.907	6.863	13.855
BTC-Shanghai	0.59	0.19	1.0003	0.087	0.087
AIC	0.815	1.603	0.000	1.826	3.826
BIC	5.723	6.511	4.907	6.733	13.641
BTC-Moex	1.513**	0.330**	1.18**	0.2610**	0.2610**
AIC	-1.026	1.338	-0.378	1.470	3.478
BIC	3.881	6.246	4.529	6.385	13.293

***, **, * indicates significance at 1%, 5% and 10% level respectively

Source: Authors Preparations

Table 11 presents the copula estimates between gold and stock market indices during the sovereign debt crisis. Although the Gumbel copula yields the lowest AIC and BIC values, indicating the best overall fit, none of the estimated dependence parameters are statistically significant. This suggests the absence of any robust co-movement between gold and equity markets during this period. The lack of significant dependence indicates that gold's returns were largely independent of stock market fluctuations, a pattern consistent with its traditional safe-haven role. However, since the estimated coefficients are not statistically significant, these results should be interpreted with caution and viewed as supportive, but not conclusive, evidence of gold's stability during periods of financial stress.

Table 11. Estimation of the parameters of the different copulas between the gold and the stock market indices during the sovereign crisis

	Archimedean copulas			Elliptical copulas	
	Frank	Clayton	Gumbel	Normal	Student
BTC –Dax	0.052	0.032	1.006	0.0098	0.0092
AIC	1.894	1.935	-0.012	1.980	3.981
BIC	6.802	6.842	4.895	6.888	13.797
BTC-Cac40	0.203	0.062	1.01	0.033	0.033
AIC	1.593	1.874	-0.023	1.934	3.934
BIC	6.501	6.782	4.884	6.841	13.749
BTC-Ibex35	-0.26	1.45 ^E -6	1	-0.068	-0.068
AIC	2.528	2.000	0.000	138.0	4.136
BIC	7.436	6.907	4.907	142.90	13.951
BTC-Ftse100	0.12	0.11	1.01	0.05	0.04
AIC	1.747	1.778	-0.027	1.900	3.920
BIC	6.655	6.686	4.880	6.807	13.735
BTC-S&P500	-0.25	0.11	1.01	0.025	-0.033
AIC	2.512	1.774	-0.023	1.950	4.066
BIC	7.420	6.682	4.883	6.857	13.881
BTC-Nikkei225	-1.53	1.45 ^E -6	1	-0.20	-0.23
AIC	5.077	2.000	0.000	2.406	4.470
BIC	9.985	6.907	4.907	7.313	14.285
BTC-Ibovespa	0.33	0.096	1.04	0.067	0.064
AIC	1.325	1.807	-0.081	1.866	3.872
BIC	6.233	6.715	4.826	6.773	13.687
BTC-Nifty50	-0.718	0.020	1	-0.053	-0.102
AIC	3.436	1.959	0.000	2.106	4.204
BIC	8.343	6.867	4.907	7.013	14.019
BTC-Shanghai	-0.64	1.45 ^e -6	1.01	-0.07	-0.089
AIC	3.287	2.000	-0.025	2.140	4.178
BIC	8.195	6.907	4.882	7.047	13.993
BTC-Moex	0.185	0.074	1.01	0.046	0.039
AIC	1.629	1.850	-0.039	1.908	3.922
BIC	6.536	6.758	4.867	6.815	13.737

Source: Authors Preparations

Table 12 reports the copula estimates between gold and stock market indices during non-crisis periods. Across all pairs, the Gumbel copula parameter equals 1, which by definition indicates

statistical independence and the absence of upper-tail dependence. Similarly, the Frank and Gaussian copulas produce near-zero or slightly negative parameters, none of which are statistically significant. These findings confirm that, under tranquil market conditions, gold exhibits no significant co-movement with equity markets, thereby confirming its behavior as an independent asset. This independence supports gold's role as a portfolio diversification instrument, although there is no evidence of strong dependence structures or tail linkages with stock indices during stable periods.

Table 12. Estimation of the parameters of the different copulas between Gold and the stock market indices without crisis

	Archimedean copulas			Elliptical copulas	
	Frank	Clayton	Gumbel	Normal	Student
BTC –Dax	-0.13	1.45 ^{e-6}	1	-0.041	-0.036
AIC	2.270	2.000	0.000	2.082	4.072
BIC	7.178	6.907	4.907	6.989	13.887
BTC-Cac40	-0.51	1.45 ^{e-6}	1	-0.084	-0.085
AIC	3.080	2.000	0.000	2.168	4.170
BIC	7.938	6.907	4.907	7.075	13.985
BTC-Ibex35	-0.13	1.45 ^{e-6}	1	-0.024	-0.023
AIC	2.260	2.000	0.000	2.084	4.072
BIC	7.169	6.907	4.907	6.991	13.887
BTC-Ftse100	-0.05	1.45 ^{e-6}	1	-0.027	-0.027
AIC	2.118	2.000	0.000	2.048	4.046
BIC	7.025	6.907	4.907	6.955	13.861
BTC-S&P500	-0.079	1.45 ^{e-6}	1	-0.027	-0.027
AIC	2.158	2.000	0.000	2.054	4.054
BIC	7.065	6.907	4.907	6.961	13.869
BTC-Nikkei225	-0.3193	1.45 ^{e-6}	1	-0.0673	-0.0612
AIC	2.638	2.000	0.000	2.134	4.122
BIC	7.546	6.907	4.907	7.042	13.937
BTC-Ibovespa	-0.259	1.45 ^{e-6}	1	-0.041	-0.041
AIC	2.519	2.000	0.000	2.082	4.082
BIC	7.427	6.907	4.907	6.989	13.897
BTC-Nifty50	-0.089	1.45 ^{e-6}	1	-0.021	-0.020
AIC	2.179	2.000	-0.014	2.042	4.040
BIC	7.087	6.907	4.893	6.949	13.855
BTC-Shanghai	0.10	0.026	1	0.014	0.014
AIC	1.795	1.947	0.000	1.972	3.972
BIC	6.703	6.855	4.907	6.879	13.787
BTC-Moex	-0.45	1.4 ^{e-6}	1	-0.074	-0.075
AIC	2.910	2.000	0.000	2.148	4.150
BIC	7.818	6.907	4.907	7.055	13.965

Source: Authors Preparations

Table 13 shows that during the COVID-19 crisis, the Gumbel copula provides the best fit for modeling gold–stock market dependence, as indicated by the lowest AIC and BIC values across most pairs (e.g., DAX, CAC40, S&P500, FTSE100, Shanghai, Nikkei225). While the Gumbel copula is suited to capturing upper-tail dependence, the estimated parameters are generally close

to the lower bound (value = 1), indicating weak or near-independence. In contrast, the Frank copula yields negative dependence parameters for several indices, particularly the Ibex35, S&P 500, FTSE 100, CAC 40, DAX, Nifty 50, and Moex, suggesting a mild inverse association between gold and equity markets. However, none of these coefficients are statistically significant, meaning that the observed negative signs should be interpreted only as indicative patterns rather than robust evidence. Overall, the predominance of weak and mostly negative dependence across copulas is consistent with gold's traditional safe-haven behavior, implying that during the pandemic, gold tended to move independently or slightly inversely to stock markets, even though the relationships lack statistical significance.

Table 13. Estimation of the parameters of the different copulas between the Gold and the stock market indices during the COVID-19

	Archimedean copulas			Elliptical copulas	
	Frank	Clayton	Gumbel	Normal	Student
BTC –Dax	-0.623	0.016	1	-0.039	-0.069
AIC	3.246	1.967	0.000	2.078	4.138
BIC	8.154	6.875	4.907	6.985	13.953
BTC-Cac40	-0.406	1.45e-6	1	-0.065	-0.067
AIC	2.813	2.000	0.000	2.130	4.134
BIC	7.721	6.907	4.907	7.037	13.949
BTC-Ibex35	-0.34	0.02	1	-0.017	-0.017
AIC	2.682	1.958	0.000	2.034	4.034
BIC	7.590	6.866	4.907	6.941	13.849
BTC-Ftse100	-0.72	1.45e-6	1	-0.11	-0.12
AIC	3.453	2.000	0.000	2.236	4.246
BIC	8.361	6.907	4.907	7.143	14.061
BTC-S&P500	-0.266	1.45e-6	1	-0.036	-0.038
AIC	2.532	2.000	0.000	2.072	4.076
BIC	7.439	6.907	4.907	6.979	13.891
BTC-Nikkei225	1.398	0.235	1.14	0.20*	0.20*
AIC	-0.796	1.528	-0.298	1.592	3.600
BIC	4.111	6.436	4.609	6.499	13.415
BTC-Ibovespa	0.35	0.104	1.08	0.102	0.063
AIC	1.287	1.791	-0.0171	1.796	3.874
BIC	6.194	6.699	4.736	6.703	13.689
BTC-Nifty50	-0.31	0.05	1.03	0.016	-0.052
AIC	2.636	1.899	-0.073	1.968	1.104
BIC	7.543	6.807	4.834	6.875	13.919
BTC-Shanghai	0.94	0.27	1.10	0.17*	0.14
AIC	0.102	1.415	-0.215	1.660	3.720
BIC	5.010	6.359	4.692	6.567	13.535
BTC-Moex	-0.39	1.45e-6	1	-0.078	-0.078
AIC	2.794	2.000	0.000	2.156	4.156
BIC	7.701	6.907	4.907	7.063	13.971

Source: Authors Preparations

6. DISCUSSION

The empirical results provide important insights into the diversification and safe-haven properties of gold and Bitcoin across different market contexts and geographic regions. Consistent with previous studies (Baur & Lucey, 2010; Belhadj et al., 2021), gold confirms its traditional role as a reliable safe-haven asset (Belhadj & Ben Hamad, 2025). In both developed and emerging markets, gold shows generally weak or negative dependence, particularly during periods of financial turmoil such as the sovereign debt crisis and the COVID-19 pandemic (Belkhir & Masmoudi, 2025). This persistent decoupling highlights its ability to remain detached from equity market fluctuations, reinforcing its status as a safe-haven asset and a preferred instrument for risk-averse investors in times of uncertainty. In contrast, Bitcoin exhibits more complex and evolving behavior. During calm periods, it shows near-independence from stock markets, suggesting some diversification potential. However, during systemic shocks such as the COVID-19 crisis, its behavior changes: moderate but asymmetric dependencies appear with certain developed indices (notably the CAC 40, FTSE 100, and MOEX). These links, although weak, reflect a temporary loss of its safe-haven role. Overall, Bitcoin behaves more like a risky asset integrated into financial markets, with correlations strengthening as global volatility increases. This finding aligns with the observations of Zhao (2022) and Bouri et al. (2017), who emphasize the contextual and unstable nature of Bitcoin's hedging capacity. One of the main contributions of this study lies in the joint analysis of gold and Bitcoin across developed and emerging markets, covering three distinct sub-periods: the sovereign debt crisis, a tranquil phase, and the COVID-19 pandemic. This approach highlights regional differences and crisis-specific dynamics often overlooked in previous literature. The results confirm that gold's safe-haven role is robust and universal, whereas Bitcoin's behavior remains unstable and sensitive to market conditions (Cocco et al., 2022; Dyhrberg, 2016; Pham et al., 2020). From a practical standpoint, these findings suggest that gold should remain a cornerstone of risk management strategies, while Bitcoin may be considered a speculative or complementary asset, but not a substitute for gold. Policymakers and financial institutions should exercise caution when portraying Bitcoin as a stable asset class, particularly during periods of heightened uncertainty or financial contagion (Schär, 2021; Cheah & Fry, 2015; Akhtaruzzaman et al., 2020). Despite its contributions, this research has certain limitations. The use of a static copula framework, while effective in capturing nonlinear and asymmetric dependencies, does not account for time-varying dynamics. Extending the analysis to dynamic copula models or regime-switching frameworks could offer richer insights. Furthermore, since the sample ends in May 2020, subsequent events such as the post-pandemic recovery, geopolitical shocks, or monetary tightening may have altered dependence structures. Including other asset classes, such as bonds or commodities, could also provide a more comprehensive understanding of Bitcoin's role within diversified portfolios. In summary, the results reinforce the historical role of gold as a traditional safe-haven asset, while Bitcoin's position remains uncertain and context-dependent. Its growing institutional adoption, however, warrants continued attention, as its progressive integration into global financial markets may eventually reshape its hedging and diversification potential.

7. CONCLUSION

This study examined the role of Bitcoin as a potential safe-haven and diversification instrument during the COVID-19 financial crisis, in comparison with gold. By combining an EGARCH model with a copula-based framework, the analysis captured time-varying, nonlinear, and tail dependencies between assets across both developed and emerging equity markets. The findings indicate that gold consistently preserves its traditional safe-haven characteristics, maintaining weak or negative dependence with stock markets even during periods of severe financial stress.

In contrast, Bitcoin's behavior remains unstable and context-dependent, offering only limited diversification benefits under specific conditions. These results suggest that Bitcoin should be incorporated cautiously into portfolio management strategies, as it cannot yet replace traditional safe-haven assets such as gold during times of systemic turmoil. Nevertheless, this study is not without limitations. Its focus on the COVID-19 period and the exclusion of other asset classes limit the generalizability of the findings. Moreover, while the copula framework effectively captures nonlinear dependencies, it does not fully account for regime shifts or dynamic structural changes.

Future research could extend the sample to include the post-COVID period (2021–2024) and investigate the evolving behavior of Bitcoin during new macro-financial regimes. Incorporating rolling or time-varying copulas, alternative marginal specifications (e.g., skew-t EGARCH), and out-of-sample portfolio experiments would further strengthen the robustness and practical relevance of these results.

Data availability

The authors do not have permission to share data.

Conflict of interest

The authors reported no potential conflict of interest.

REFERENCES

- Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2020). Financial contagion during COVID-19 crisis. *Finance Research Letters*, 38, 101604. <https://doi.org/10.1016/j.frl.2020.101604>
- Aloui, R., Aïssa, M. S. B., & Nguyen, D. K. (2013). Conditional dependence structure between oil prices and exchange rates: A copula-GARCH approach. *Journal of International Money and Finance*, 32, 719–738. <https://doi.org/10.1016/j.jimonfin.2012.06.006>
- Areal, N., Ferreira, P., & Nuno, T. (2015). Gold as a hedge or safe haven asset for the global stock market. *Journal of Economics and Business*, 79, 1–23. <https://doi.org/10.1016/j.jeconbus.2015.05.002>
- Areal, N., Oliveira, B., & Sampaio, R. (2015). When times get tough, gold is golden. *The European Journal of Finance*, 21(6), 507–526. <https://doi.org/10.1080/1351847X.2013.854821>
- Baillie, R. T., & Bollerslev, T. (1992). Prediction in dynamic models with time-dependent conditional variances. *Journal of Econometrics*, 52(1–2), 91–113. [https://doi.org/10.1016/0304-4076\(92\)90066-Z](https://doi.org/10.1016/0304-4076(92)90066-Z)
- Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, 45(2), 217–229. <https://doi.org/10.1111/j.1540-6288.2010.00244.x>
- Baur, D. G., & Lucey, B. M. (2010). Is gold a safe haven? *International Review of Financial Analysis*, 19(4), 219–228. <https://doi.org/10.1016/j.irfa.2010.07.007>
- Belhadj, H., & Ben Hamad, S. (2021). Gold and Bitcoin are Safe-haven? Evidence from Developed and Emerging Market Indices During the COVID-19 Bear Market. In *COVID-19 Pandemic and Energy Markets: Commodity Markets, Cryptocurrencies and Electricity Consumption under the COVID-19*, 55–86. World Scientific Publishing Co. https://doi.org/10.1142/9789811239618_0005
- Belhadj, H., & Ben Hamad, S. (2025). Does gold improve international diversification of US Portfolio?. *SN Business & Economics*, 5(11), 1–21. <https://doi.org/10.1007/s43546-025-00932-6>
- Belkhir, N. (2025). Dynamic interconnectedness and portfolio implications of bitcoin, gold, currencies, and TASI: A TVP-VAR approach, *Zhongguo Kuangye Daxue Xuebao*, 30(1), 224–237.
- Belkhir, N., & Masmoudi, W. K. (2025). Dynamic spillovers between G7 stock markets and precious metals: A time-varying analysis of gold and silver. *Journal of Asian Scientific Research*, 15(3), 591–607. <https://doi.org/10.55493/5003.v15i3.5601>
- Belkhir, N., Syed, A. A., Benyoussef, S., & Jeribi, A. (2025). Artificial Intelligence vs the American Market: Unveiling Shock Transfer Mechanisms to Emerging Markets Through Quantile VAR and Frequency Analysis. *Emerging Markets Finance and Trade*, 1–26. <https://doi.org/10.1080/1540496X.2025.2538665>
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307–327. [https://doi.org/10.1016/0304-4076\(86\)90063-1](https://doi.org/10.1016/0304-4076(86)90063-1)
- Bollerslev, T. (1987). A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return. *The Review of Economics and Statistics*, 69(3), 542–547. <https://doi.org/10.2307/1925546>
- Bouri, E., Molnár, P., Azzi, G., & Roubaud, D. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, 20, 192–198. <https://doi.org/10.1016/j.frl.2016.09.025>
- Cocco, L., Boudt, K., & Van Hirtum, L. (2022). Bitcoin as a safe haven in the pandemic: Evidence from the COVID-19 crisis. *Economics Letters*, 209, 110089. <https://doi.org/10.1016/j.econlet.2021.110089>
- Conlon, T., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. *Finance Research Letters*, 35, 101607. <https://doi.org/10.1016/j.frl.2020.101607>
- Corbet, S., Larkin, C., & Lucey, B. M. (2018). The volatility of Bitcoin and its role in financial markets. *International Review of Financial Analysis*, 59, 105–117. <https://doi.org/10.1016/j.irfa.2018.08.010>

- Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, 28–34. <https://doi.org/10.1016/j.econlet.2018.01.004>
- Dyhrberg, A. H. (2016). Hedging capabilities of Bitcoin: Is it the virtual gold? *Finance Research Letters*, 16, 139–144. <https://doi.org/10.1016/j.frl.2015.10.025>
- Henriksen, E. (2018). Commodities and diversification in stock markets. *Journal of Financial Markets*, 41, 48–70. <https://doi.org/10.1016/j.finmar.2018.01.001>
- Henriksen, T. E. S. (2018). Properties of long/short commodity indices in stock and bond portfolios. *The Journal of Alternative Investments*, 21(1), 6–22. <https://doi.org/10.3905/jai.2018.1.060>
- Jondeau, E., & Rockinger, M. (2006). The copula-GARCH model of conditional dependencies: An international stock market application. *Journal of International Money and Finance*, 25(5), 827–853. <https://doi.org/10.1016/j.jimonfin.2006.04.007>
- Kristoufek, L. (2020). Grandpa, grandpa, tell me the one about Bitcoin being a safe haven: Evidence from the COVID-19 pandemics. *arXiv preprint*, arXiv:2004.00047. <https://arxiv.org/abs/2004.00047>
- Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, 59(2), 347–370. <https://doi.org/10.2307/2938260>
- Nedved, M., & Kristoufek, L. (2023). Safe havens for Bitcoin. *Finance Research Letters*, 51(C). <https://doi.org/10.1016/j.frl.2022.103436>
- Patton, A. J. (2006). Modelling asymmetric exchange rate dependence. *International Economic Review*, 47(2), 527–556. <https://doi.org/10.1111/j.1468-2354.2006.00387.x>
- Pham, L. (2020). Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. *Finance Research Letters*, 35, 101607. <https://doi.org/10.1016/j.frl.2020.101607>
- Schär, F. (2021). Decentralized finance: On blockchain- and smart contract-based financial markets. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3571335>
- Shahzad, S. J. H., Adekoya, A. F., & Bouri, E. (2019). Financialization and the role of gold: Evidence from the global financial crisis. *Resources Policy*, 62, 30–42. <https://doi.org/10.1016/j.irfa.2019.01.002>
- Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019). Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis*, 63, 322–330. <https://doi.org/10.1016/j.irfa.2019.01.002>
- Cheah, E.-T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets. An empirical investigation into the fundamental value of Bitcoin. *Economics Letters*, 130, 32–36. <https://doi.org/10.1016/j.econlet.2015.02.029>
- Tarchella, S., Khalfaoui, R., & Hammoudeh, S. (2024). The safe haven, hedging, and diversification properties of oil, gold, and cryptocurrency for the G7 equity markets: Evidence from the pre- and post-COVID-19 periods. *Research in International Business and Finance*, 67, 102125. <https://doi.org/10.1016/j.ribaf.2023.102125>
- Vankov, N., & Lukarev, V. (2025). Implementation of Smart IoT Technologies on the Bulgarian Market - An Innovative Approach for Economic Sustainability And Environmental Benefits. *Collection of papers new economy*, 3(1), 101-116. <https://doi.org/10.61432/CPNE0301101v>
- Widjaja, M., Gaby, & Havidz, S. A. H. (2024). Are gold and cryptocurrency a safe haven for stocks and bonds? Conventional vs Islamic markets during the COVID-19 pandemic. *European Journal of Management and Business Economics*, 33(1), 96–115. <https://doi.org/10.1108/EJM-BE-05-2022-0135>
- Zhao, J. (2022). Do economic crises cause trading in Bitcoin? *Review of Behavioral Finance*, 14(4), 465–490. <https://doi.org/10.1108/RBF-02-2022-0048>

Appendix

Table2. Best ARMA-EGARCH model equipped for each of the time series considered during the sovereign crisis

During the sovereign crisis	
Time series	Suggested model
Bitcoin	ARMA (4,2) EGARCH(1,1)
Lingot	ARMA (1,1) EGARCH(1,1)
Dax	ARMA (2,2) EGARCH(1,1)
Cac40	ARMA (3,3) EGARCH(1,1)
FTSE100	ARMA (3,2) EGARCH(1,1)
Ibex 35	ARMA (2,2) EGARCH(1,1)
S&P500	ARMA (1,1) EGARCH(1,1)
Nikkei225	ARMA (2,2) EGARCH(1,1)
FTSE Brazil	ARMA (4,4) EGARCH(1,1)
Nifty50	ARMA (2,2) EGARCH(1,1)
Shanghai index	ARMA (1,1) EGARCH(1,1)
Moex	ARMA (2,2) EGARCH(1,1)

Source: Authors Preparations

Table 3. Best ARMA-EGARCH model equipped for each of the time series considered during the non-crisis period

The non-crisis period	
Time series	Suggested model
Bitcoin	ARMA (3,3) EGARCH(1,1)
Lingot	ARMA (1,2) EGARCH(1,1)
Dax	ARMA (2,2) EGARCH(1,1)
Cac40	ARMA (2,2) EGARCH(1,1)
Ftse100	ARMA (2,2) EGARCH(1,1)
Ibex 35	ARMA (2,2) EGARCH(1,1)
S&P500	ARMA (1,1) EGARCH(1,1)
Nikkei225	ARMA (3,2) EGARCH(1,1)
FTSE Brazil	ARMA (2,2) EGARCH(1,1)
Nifty50	ARMA (3,2) EGARCH(1,1)
Shanghai index	ARMA (3,2) EGARCH(1,1)
Moex	ARMA (1,1) EGARCH(1,1)

Source: Authors Preparations

Table 4. Best ARMA-EGARCH model equipped for each of the time series considered during the COVID-19 crisis

During the COVID-19 crisis	
Time series	Suggested model
Bitcoin	ARMA (3,3) EGARCH(1,1)
Lingot	ARMA (1,1) EGARCH(1,1)
Dax	ARMA (2,2) EGARCH(1,1)
Cac40	ARMA (2,2) EGARCH(1,1)
Ftse100	ARMA (2,2) EGARCH(1,1)
Ibex 35	ARMA (2,0) EGARCH(1,1)
S&P500	ARMA (0,2) EGARCH(1,1)
Nikkei225	ARMA (2,2) EGARCH(1,1)
FTSE Brazil	ARMA (4,3) EGARCH(1,1)
Nifty50	ARMA (2,2) EGARCH(1,1)
Shanghai index	ARMA (0,1) EGARCH(1,1)
Moex	ARMA (2,2) EGARCH(1,1)

Source: Authors Preparations

Table 5. Estimation results of the ARMA-EGARCH model during the sovereign crisis

During the sovereign crisis						
	S&P500	NIKKEI225	DAX	CAC40	FTSE100	IBEX35
C	0.006**	0.002***	0.0003	4.99 ^E -05	0.0004	-0.0005
AR(1)	0.74***	0.24	0.96***	0.90***	1.51***	1.12***
AR(2)		0.70***	-0.96***	0.23	-0.76***	-0.93***
AR(3)				-0.57***	-0.09	
AR(4)						
MA(1)	-0.83***	-0.36	-0.94***	-1.05***	-1.65***	-1.12***
MA(2)		-0.61**	0.98***	-0.05	0.97***	0.97***
MA(3)				0.60**		
MA(4)						
W	-1.24***	-14.42***	-0.25	-0.87***	-1.44***	0.012
α	0.003	0.24***	0.027	0.10**	0.12	-0.015
γ	-0.25***	0.19***	-0.11***	-0.30***	-0.16***	-0.10***
β	0.87***	-0.67***	0.97***	0.92***	0.86***	0.99***
MV	943.89	756.60	859.67	831.43	929.46	764.51
D-W	1.97	1.96	1.95	1.89	1.85	1.95
B	BITCOIN	LINGOT	MOEX	FTSE BRA-ZIL	SHANGHAI	NIFY50
C	0.006	-0.001**	-0.0002	-0.0002	0.0008	0.0006
AR(1)	-0.72***	-0.73***	-1.18***	0.19***	0.96***	0.78***
AR(2)	-0.76***		-0.92***	0.20***		-0.93***
AR(3)	0.18**			0.21***		
AR(4)	-0.04			-0.95***		
MA(1)	0.99***	0.56***	1.25***	-0.27***	-0.98***	-0.77***
MA(2)	0.97***		0.98***	-0.20***		0.98***
MA(3)				-0.28***		
MA(4)				0.98***		
W	-0.7***	-0.81***	-6.26	-14.68***	-1.95***	-13.89***
α	0.48***	0.045	-0.10	0.07	-0.07	-0.32***
γ	0.099**	-0.23***	0.062	0.17**	-0.32***	0.16*
β	0.94***	0.91***	0.30	-0.58**	0.78***	-0.46*
MV	486.34	830.10	846.32	852.23	843.45	909.74
D-W	1.74	1.67	2.02	1.90	1.97	1.91

***, **, * indicates significance at 1%, 5% and 10% level respectively.

Source: Authors Preparations

Table 6. Estimation results of the ARMA-EGARCH model during the non-crisis period

The non-crisis period						
	S&P500	NIKKEI225	DAX	CAC40	FTSE100	IBEX35
C	0.00047***	0.00037	0.0002	0.0001	-9.09 ^E -05	-0.0001**
AR(1)	0.96***	-1.59***	1.78***	1.58***	1.12***	1.43***
AR(2)		-0.77***	-0.98***	-0.98***	-0.99***	-0.44
AR(3)		0.0033				
AR(4)						
MA(1)	-0.98***	1.60***	-1.79***	-1.58***	-1.11***	-1.43***
MA(2)		0.77***	0.99***	0.98***	0.98***	0.44
MA(3)						
MA(4)						
W	-0.97***	-0.69***	-0.46***	-0.51***	-0.76***	-0.49***
α	0.17***	0.15***	0.12***	0.14***	0.14***	0.146***
γ	-0.23***	-0.16***	-0.12***	-0.16***	-0.17***	-0.09***
β	0.91***	0.96***	0.96***	0.95***	0.93***	0.95***
MV	6075.7	5300.3	5463.81	5562.1	5924.08	5352.4
D-W	1.97	2.12	2.03	2	1.97	1.97
	BITCOIN	LINGOT	MOEX	FTSE BRA-ZIL	SHANGHAI	NIFY50
C	0.001	0.002***	0.0003***	0.0004	0.0001*	0.0003
AR(1)	0.20	-0.27***	0.98***	-1.6***	0.02	0.62***
AR(2)	0.81***			-0.98***	0.98***	-1.01***
AR(3)	-0.035				-0.022	0.09***
AR(4)						
MA(1)	-0.18	-0.32***	-0.99***	1.60***	-0.002	-0.53***
MA(2)	-0.77***	0.27***		0.99***	-0.99***	0.95***
MA(3)	-0.01					
MA(4)						
W	-0.68***	-1.02***	-0.48***	-0.23***	-0.10***	-0.43***
α	0.26***	0.81***	0.11***	0.08***	0.11***	0.10***
γ	-0.02**	0.65***	-0.08***	-0.037***	0.02***	-0.14***
β	0.91***	0.91***	0.95***	0.98***	0.99***	0.96***
MV	2854.1	4201.94	5392.7	4977.9	5254.9	5766.5
D-W	2.13	2.01	2	2.02	1.93	2.03

***, **, * indicates significance at 1%, 5% and 10% level respectively.

Source: Authors Preparations

Table 7. Estimation results of the ARMA-EGARCH model during the COVID-19 crisis

During COVID-19 crisis						
	S&P500	NIKKEI225	DAX	CAC40	FTSE100	IBEX35
C	-0.001***	-0.002***	-0.003	-0.0007	-0.001***	-0.003***
AR(1)		-0.100	-0.57***	-9.23 ^E -05	-0.45***	0.001
AR(2)			-0.79***	0.80***	-0.91***	
AR(3)						
AR(4)						
MA(1)	-0.12		0.67***	0.02	0.51***	0.02
MA(2)	0.16*		0.89***	-0.92***	0.86***	
MA(3)						
MA(4)						
W	-0.27***	-0.15	-0.29*	-0.41	-0.23***	-0.18
α	-0.23***	-0.24	-0.19	-0.40**	-0.20***	-0.22***
γ	-0.5***	-0.29***	-0.34***	-0.46***	-0.25***	-0.20***
β	0.93***	0.95***	0.93***	0.91***	0.94***	0.94***
MV	280.67	280..79	257.9	271.50	277.06	266.63
D-W	2.5	1.47	2.17	1.99	2.16	2.28
	BITCOIN	LINGOT	MOEX	FTSE BRA-ZIL	SHANGHAI	NIFY50
C	0.007**	0.001***	-0.0039***	-0.002	-0.002**	-0.003***
AR(1)	-0.095	0.79***	0.61	-0.32		0.72***
AR(2)	0.031		0.20	-0.62		-0.82***
AR(3)	-0.033			0.16		
AR(4)				0.12		
MA(1)	-0.14	-0.92***	-0.61	0.24	-0.009	-0.86***
MA(2)	0.02		-0.18	0.62*		0.93***
MA(3)	-0.05			-0.34		
MA(4)						
W	-5.45***	-3.40***	-0.22	-0.43**	-1.12***	-0.15
α	-1.04***	-1.36***	-0.15	-0.13	-0.11*	-0.16
γ	-0.044	-0.71***	-0.27***	-0.43***	-0.54***	-0.28***
β	0.0009	0.45***	0.95***	0.92***	0.84***	0.95***
MV	152.42	273.56	278.12	231.14	309.27	262.96
D-W	1.84	1.97	2.10	2.38	2.21	2.14

***, **, * indicates significance at 1%, 5% and 10% level respectively.

Source: Authors Preparations