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Volatility contagion between Cryptocurrencies, gold and stock markets pre-and-during COVID-19: Evidence using DCC-GARCH and Cascade-Correlation Network

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Volatility contagion among cryptocurrencies, gold, and stock markets before and during COVID-19: Evidence using DCC-GARCH, wavelet coherence, and cascade-correlation network

ABSTRACT

The rapid rise of Bitcoin and its increasing global adoption has raised concerns about its impact on traditional markets, particularly in periods of economic turmoil and uncertainty such as the COVID-19 pandemic. This study examines the extent of the volatility contagion from the Bitcoin market to traditional markets, focusing on gold and six major stock markets (Japan, USA, UK, China, Germany, and France) using daily data from January 2, 2011, to June 2, 2022, with 2,958 daily observations. We employ DCC-GARCH, wavelet coherence, and cascade-correlation network models to analyze the relationship between Bitcoin and those markets. Our results indicate long-term volatility contagion between Bitcoin and gold and short-term contagion during periods of market turmoil and uncertainty. We also find evidence of long-term contagion between Bitcoin and the six stock markets, with short-term contagion observed in Chinese and Japanese markets during COVID-19. These results suggest a risk of uncontrollable threats from Bitcoin volatility and highlight the need for measures to prevent infection transmission to local stock markets. Hedge funds, mutual funds, and individual and institutional investors can benefit from using our findings in their risk management strategies. Our research confirms the utility of the cascade-correlation network model as an innovative method to investigate intermarket contagion across diverse conditions. It holds significant implications for stock market investors and policymakers, providing evidence for potentially using cryptocurrencies for hedging, for diversification, or as a safe haven.

Keywords: Cryptocurrencies; Gold; Stock *Markets; COVID-19; Cascade-Correlation network*

JEL Classification: C45; D53; E42; G10

I. INTRODUCTION

Analysis of volatility spillovers among cryptocurrencies, gold, and stock markets during the COVID-19 pandemic is particularly interesting for investment funds, hedge funds, and individual investors, as it offers valuable insights for hedging, diversification, and risk management purposes during uncertainty and crisis (Cui & Maghyereh, 2022; Das & Gangopadhyay, 2023; Jain et al., 2023). Cryptocurrencies are controversial, with some policymakers and scholars regarding them as a disruptive technology with both benefits and drawbacks; this study contributes to the ongoing debate about their role in the global financial system. While cryptocurrencies have the potential to revolutionize payment systems and foster innovation, they also pose risks to national security, financial stability, and consumer protection, as documented in previous research (Fratrič et al., 2022; Guesmi et al., 2019b; Haykir & Yagli, 2022; Özdemir, 2022; Qarni & Gulzar, 2021; Shahzad et al., 2021; Sruthi & Shijin, 2020). This study examines the dynamics of volatility contagion between cryptocurrencies and traditional financial assets such as gold and stock indices to shed light on interdependencies and transmission channels among these markets and guide investment strategies and policy interventions.

The ongoing debate over the value and role of cryptocurrencies has been fueled by contrasting views among prominent figures in the business and investment communities (Bazzanella & Gangemi, 2023; Wu et al., 2021; Xiao et al., 2021, P. Xie et al., 2019; Tosunoğlu et al., 2023). On May 22, 2021, Elon Musk, the founder of SpaceX and CEO of Tesla, tweeted his support for cryptocurrencies, declaring a "battle" between digital currencies and fiat currencies.[1] In contrast, Warren Buffett, the Chairman, and CEO of Berkshire Hathaway, expressed his

[1] See https://www.reuters.com

skepticism about cryptocurrencies at the company's annual shareholder meeting on April 20, 2022, stating that he would reject an offer to buy all the world's bitcoins for USD 25, as it is a nonproductive asset that generates no tangible value.[2] However, some observers view Bitcoin as a new form of gold, or "digital gold," due to its similarities to the precious metal, such as the mining process, decentralized ownership, and limited supply. Nevertheless, notable differences are evident between gold and Bitcoin, including the tangibility of gold versus the intangibility of Bitcoin and the potential for Bitcoin imitation by issuing similar digital coins (Baur & Hoang, 2021).

Bitcoin was introduced in 2009 as a decentralized alternative to traditional currencies (Nakamoto, 2008). With a market capitalization of USD 390 billion and a circulating supply of 19,075,131 BTC as of June 23, 2022,[3] Bitcoin accounts for 43% of the total market capitalization of 9,928 cryptocurrencies. From the beginning of 2010 to November 2021, the price of Bitcoin surged from a few cents to a peak of USD 68,000 (Ahmed, 2022). Due to its popularity, Bitcoin has been adopted as a payment tool by several countries and companies and emerged as the most widely used cryptocurrency worldwide, ranking first among cryptocurrencies based on market capitalization for a decade (Chkili et al., 2021). Hence, this study uses Bitcoin as a proxy for cryptocurrencies.

The existing empirical literature suggests four channels for examining the relationship between Bitcoin and gold. The first channel examines Bitcoin as a safe haven asset. Some studies suggest that Bitcoin can be used as a safe haven asset in times of market uncertainty (Brière et al., 2015; Feng et al., 2018; Kang et al., 2020; Urquhart & Zhang, 2019), whereas others find no

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[2] See https://www.cnbc.com
[3] See https://coinmarketcap.com

evidence supporting this claim (Bouoiyour & Selmi, 2015; Long et al., 2021). The second channel explores Bitcoin as a hedging tool, with Guesmi et al. (2019) suggesting that Bitcoin can be an effective hedging instrument. The third channel investigates the Bitcoin and gold relationship, with studies suggesting that Bitcoin behavior differs from that of gold (Klein et al., 2018), whereas others find no relationship (Baur, Dimpfl, et al., 2018; Kristoufek, 2015) or a weak relationship (Giudici & Abu-Hashish, 2019; Gkillas et al., 2020). Similarly, Ji et al. (2018) determine that the Bitcoin market is isolated from other financial markets, including gold, with a delayed causal relationship between Bitcoin and other financial assets. The fourth channel examines volatility transmission between Bitcoin and gold, with Bouri et al. (2018) suggesting that gold exhibits greater volatility spillover effects on Bitcoin than the other way around.

The empirical literature has identified four channels for examining the relationship between Bitcoin and the stock market. First, studies have examined whether Bitcoin can be used to hedge stock market risks. While some studies suggest that Bitcoin can serve as a hedging tool against equities (Dyhrberg, 2016a; Fang et al., 2019; Guesmi et al., 2019b), others have indicated otherwise (Feng et al., 2018; Klein et al., 2018). Second, research has investigated the possibility of using Bitcoin as a diversifier, and several studies have suggested its potential to diversify portfolios (Baur, Hong, et al., 2018; Brière et al., 2015; Corbet et al., 2019; Feng et al., 2018; Kajtazi & Moro, 2019; Kang et al., 2020). The third channel has explored the correlation between Bitcoin and stock markets. Whereas Bouri et al. (2018) found evidence of a correlation between Bitcoin and stock returns in China and emerging markets, Giudici and Abu-Hashish (2019) found only a weak correlation between Bitcoin and US stock market returns. Finally, research has investigated volatility transmission between Bitcoin and stock markets. Symitsi and Chalvatzis (2018) suggest long-term volatility transmission from Bitcoin to energy stocks, short-term transmission from tech stocks to Bitcoin, and shock transmissions between Bitcoin and stock indices. Conversely, Klein et al. (2018) found that Bitcoin returns respond differently to market shocks.

In December 2019, an emerging infectious disease surfaced and quickly spread worldwide. Subsequently, in March 2020, the World Health Organization (WHO) officially classified the disease as a pandemic, commonly referred to as COVID-19. This unprecedented occurrence resulted in significant economic turmoil, characterized by substantial declines in stock and oil prices (Wen et al., 2022). While previous health threats such as Ebola, Spanish flu, and SARS had created challenges for the economy, policymakers, and the public, the impact of COVID-19 was particularly severe due to increased interdependence among countries. Despite efforts by countries to mitigate the negative effects on their economies, financial markets suffered significant losses. For instance, the price of Bitcoin dropped by 63%, from USD 10,514 to USD 3,880, between February 13, 2020, and March 13, 2020, while the price of gold fell by 14%, from USD 1,689 to USD 1,451, between February 24, 2020, and March 16, 2020. Similarly, the NIKKIE 225 fell by 30%, S&P by 35%, FTSE 100 by 36%, FTSE China A50 by 19%, DAX by 38%, and CAC40 by 38% between February 24, 2020, and March 23, 2020. These losses illustrate the severe impact of the COVID-19 pandemic on global financial markets.[4]

Based on the aforementioned empirical literature, a relationships exist among Bitcoin, gold, and stock markets. There is also a possibility to use Bitcoin as a safe haven, hedging tool, or diversifier. Despite the considerably high volatility in financial markets and the collapses in stock markets and cryptocurrency prices during COVID-19, gold prices rose sharply. Furthermore,

[4] See https://www.tradingview.com

Figures 1 and 2 suggest similar volatilities for Bitcoin, gold, and the stock markets of Japan, the USA, the UK, China, Germany, and France. This implies stronger volatility contagion between January 2, 2011, and June 2, 2022. A clear gap exists in the empirical literature—to our knowledge, no investigation has been made into volatility contagion between Bitcoin and gold on the one hand and Bitcoin and stock markets on the other during COVID-19. Studying such a contagion can provide hedge funds, investment funds, and individual investors with evidence to help them build investment portfolios that employ cryptocurrencies for diversification, hedging, or as a safe haven. Such study can also benefit decision-makers and policymakers by putting preventive measures in place to prevent or reduce volatility contagion between cryptocurrencies and their respective stock markets.

INSERT FIGURE 1

Our study distinguishes itself from the research conducted by Corbet et al. (2020), Fernandes et al. (2022), Handika et al. (2019), Matkovskyy and Jalan (2019), Wang et al. (2022), F. Zhang et al. (2021), and J. Zhang and He (2021). We have incorporated both traditional methods and machine learning models, whereas they solely relied on traditional methods. This integration allows us to leverage the strengths of both approaches in our analysis. Additionally, our study diverges from studies by Handiket al. (2019) and Matkovskyy and Jalan (2019), in that we specifically examined intermarket contagion during the COVID-19 period, an element that was not explored in their studies. This temporal focus lets us capture the unique dynamics of market interconnections during that unprecedented time. Moreover, our research stands out for the breadth of the markets analyzed for contagion. We investigated contagion among cryptocurrencies, gold, and six stock markets spanning three continents. In contrast, Handika et al. (2019) primarily concentrated on cryptocurrencies and Asian markets, Corbet et al. (2020) focused on Bitcoin and

Chinese stock markets, and Wang et al. (2022) delved into US stock markets. Fernandes et al. (2022) explored contagion between cryptocurrencies and FIAT currencies, while F. Zhang et al. (2021) examined the predictive relationship between oil and stocks. Furthermore, regarding markets tested for contagion with cryptocurrencies, our study sets itself apart from the studies by Matkovskyy and Jalan (2019) and J. Zhang and He (2021) because it uniquely considers the French stock market in its analysis. This inclusion expands our investigation and provides a more comprehensive understanding of the contagion dynamics between cryptocurrencies and global markets.

The present study bridges a gap in the existing literature by investigating and providing answers to the following research questions: (1) Does short-term volatility contagion exist between cryptocurrencies and gold before and during the COVID-19 pandemic? (2) Does short-term volatility contagion exist between cryptocurrencies and stock markets in Japan, the US, the UK, China, Germany, and France before and during the COVID-19 pandemic? (3) Does long-term volatility contagion exist between cryptocurrencies and gold before and during the COVID-19 pandemic? (4) Does long-term volatility contagion exist between cryptocurrencies and stock markets in Japan, the US, the UK, China, Germany, and France before and during the COVID-19 pandemic? By investigating these research questions, this study provides insights that could benefit hedge funds, investment funds, and individual investors when building their investment portfolios, as well as decision-makers and policymakers when formulating measures to prevent or reduce volatility contagion between cryptocurrencies and their respective stock markets.

We address the aforementioned research questions through several methodological approaches. First, we use Bitcoin as a proxy for the broader cryptocurrency market, and Nikkei 225, SPX 500, FTSE 100, FTSE China A50, DAX, and CAC 40 contracts for difference (CFDs) as proxies for the Japanese, US, UK, Chinese, German, and French stock markets, respectively. Second, we employ the dynamic conditional correlation GARCH (DCC-GARCH) model, first introduced by Engle (2002), to investigate volatility contagion in both the short and the long term. Finally, to enhance the robustness of our findings, we employ the cascade-correlation network and wavelet coherence models as a mutually supportive technique.

Based on our empirical findings, we can conclude that evidence exists of short-term and long-term volatility contagion between Bitcoin, gold, and various stock markets. Specifically, we find significant long-term volatility contagion between Bitcoin and gold, which persisted over the study period spanning more than 11 years. Furthermore, our results suggest short-term volatility contagion between Bitcoin and gold during the COVID-19 pandemic, indicating the transmission of shocks from the Bitcoin market to the gold market during this period of uncertainty and panic.

We also find evidence of long-term volatility contagion between Bitcoin and the stock markets of Japan, the US, the UK, China, Germany, and France. This implies the transmission of Bitcoin volatility to these markets throughout the entire study period, as well as during the subperiods before and during COVID-19. However, we find no evidence of short-term volatility contagion between Bitcoin and these markets during the entire study period or the pre-COVID-19 subperiod, suggesting that shocks were not transmitted from the Bitcoin market to these markets during that time. Interestingly, our findings also indicate short-term volatility contagion between Bitcoin and the Chinese and Japanese stock markets during COVID-19. This suggests that Bitcoin market shocks were transmitted to the Chinese and Japanese stock markets during this period. This could possibly be explained by Bitcoin popularity among the middle class in China in 2018, which may have increased the exposure to Bitcoin market shocks. Similar reasoning may apply to the Japanese stock market.

Our investigation significantly enhances the existing literature on volatility contagion among Bitcoin, gold, and six international stock markets in several ways. First, our study extends the analysis to a longer period of more than 11 years, surpassing the previous research durations of 3 to 8 years (Lee & Kim, 2022; Zhang et al., 2021). This broader time frame provides a more comprehensive understanding of market contagion dynamics. Second, our study breaks new ground by examining volatility contagion between Bitcoin and stock markets in France. This expansion of the analysis into additional markets adds a fresh perspective to the literature. Third, our research compares volatility contagion among Bitcoin, gold, and six international stock markets both before and during the COVID-19 pandemic. This comparative approach enables a deeper understanding of the impact of market shocks and the effectiveness of various assets as safe havens during times of crisis. Fourth, we employed a diverse set of analytical models, including the DCC-GARCH, wavelet coherence, and cascade-correlation network models. The results of these implementations indicated that the cascade-correlation network model captures contagion between specific markets, the DCC-GARCH model fails to do so, and the wavelet coherence model succeeds in capturing it. These novel findings highlight the potential to employ machine learning techniques, particularly the cascade-correlation network model, to investigate contagion between markets. Finally, our use of CFDs for stock indices offers a notable advantage over previous studies that have relied on traditional indicators. CFDs enable trading 23 hours a day during trading days, aligning with the operational hours of cryptocurrencies that operate 24 hours a day. This alignment provides more accurate and real-time data for measuring and analyzing contagion effects.

In summary, our research not only extends the knowledge about volatility contagion between Bitcoin, gold, and international stock markets but also introduces new insights, comparative analyses, and advanced analytical techniques. These contributions advance the understanding of market interdependencies and offer practical implications for risk management and portfolio diversification strategies.

The rest of this paper is organized as follows. Section II describes our dataset and methodology. Section III presents and discusses our results, and Section IV concludes our work and suggests areas for future research.

II. EXPERIMENTAL DATA AND METHODOLOGY

A. Experimental data

Data are obtained from TradingView.[5] The raw data are the daily closing prices of Bitcoin as a proxy for cryptocurrencies. In addition, we freshly use the CFD daily close of gold and use Nikkei 225, SPX 500, FTSE 100, FTSE China A50, DAX, and CAC 40 CFDs as proxies for the Japanese, US, UK, Chinese, German, and French stock markets, respectively. CFD data are chosen because, as mentioned, CFDs trade 23 hours a day, even when the main markets are closed, except for weekends. This provides a more accurate measure of contagion among markets, since Bitcoin trades nearly around the clock. The dataset covers the period from January 2, 2011, to June 2, 2022, with 2,958 daily observations divided into two subsamples. The first subsample is pre-COVID-19 and covers the period from January 2, 2011, to February 23, 2020, with 589 daily observations. The second subsample is during COVID-19 and covers the period from February 24, 2020, to June 2, 2022, with 2,369 daily observations. The rationale behind examining two unbalanced time series is because three distinct price trends (uptrend, downtrend, and sideways trend) are present during the COVID-19 subperiod. To ensure the objectivity of our findings, it

[5] See https://www.tradingview.com

was necessary to compare them with observations that could capture these three trends. We identified such observations within longer time series, as depicted in Figure 2.

INSERT FIGURE 2

We started the study in 2011 because before 2011, the price of Bitcoin did not exceed 30 cents, with no significant fluctuation in price before the start of that year, as shown in Figure 3. We started the subsample during COVID-19 on February 24, 2020, because news announced by the WHO before this date had no effect on the study variables; the effect started after February 24, 2020, as shown in Figure 4. It is worth noting that the WHO declared COVID-19 an international pandemic in March 2020 (Rokicki et al., 2022).

INSERT FIGURE 3

INSERT FIGURE 4

We adopted the methodology presented by Stosic et al. (2019) to compute the logarithmic returns for each variable, as outlined below:

$$R_i(t) = \ln S_i(t + \Delta t) - \ln S_{i(t),} \tag{1}$$

where $S_i(t)$ denotes the daily closing price at time t, i represents the index of the respective time series, and Δt corresponds to a time interval of 1 day. Summary statistics of the daily return for the examined variables are reported in Panel A of Table 1, where we find that Bitcoin achieved the lowest daily return (i.e., −0.49373) and highest daily return (i.e., 0.59327) of the return series, as wel as the highest average return and volatility (i.e., mean, median, and variance values of 0.00389, 0.00259, and 0.00337, respectively). All variables have negative skewness except for Bitcoin. All return series are leptokurtic. Panel B of Table 1 presents the results of the ADF and PP unit root tests, confirming that all return series are stationary. As explained above, Figure 1 suggests that periods of Bitcoin volatility correspond to periods of similar volatility in gold and the six international stock markets. Therefore, the DCC-GARCH model is appropriate for determining whether volatility or contagion is transmitted among these markets.

INSERT TABLE 1

B. Methodology

We use DCC-GARCH, wavelet coherence, and cascade-correlation network models as mutually supportive techniques and for robustness purposes.

DCC-GARCH

Multivariate GARCH models suffer from bias when estimating parameters, while the DCC-GARCH model presented by Engle (2002) simply captures time-varying and dynamic relationships (Bouri et al., 2017). The DCC-GARCH model has been used extensively by researchers to examine contagion between markets (see, for example, Celik, 2012; Nguyen et al., 2022; Özdemir, 2022; W. Zhang et al., 2022). The DCC-GARCH model is a widely used multivariate GARCH model that enables the modeling of time-varying correlations among multiple variables in a time series. It is particularly valuable for analyzing financial markets, where the behavior of various assets is intricately interconnected and interdependent. This model effectively captures volatility and correlation dynamics, providing valuable insights into relationships between different assets. The DCC-GARCH model comprises two components: the GARCH model and the dynamic conditional correlation model. The GARCH model is employed to estimate the conditional variance of individual assets, while the dynamic conditional correlation model is employed to estimate time-varying conditional correlation among these assets. By utilizing these two components, the DCC-GARCH model provides a comprehensive understanding of volatility and correlation dynamics within financial markets. The GARCH model is an enhanced version of the autoregressive conditional heteroskedasticity (ARCH) model, designed to capture the volatility patterns in a time series by considering its own historical data. In addition to modeling volatility based on past values, the GARCH model introduces an extra element to account for the influence of previous shocks on current volatility. Specifically, the GARCH model assumes that the conditional variance of a time series at a given time *t* can be expressed as a function of its previous variances and the squared residuals or shocks from past observations:

$$v_t = \omega + \sum(\alpha_i \times \varepsilon_{(t-i)^2}) + \sum\big(\beta_i \times V_{(t-i)}\big), \tag{2}$$

where v_t represents the measure of variance at time *t*, and ω is a constant term. The model parameters α_i and β_i play a crucial role in determining the impact of the squared residuals or shocks $\varepsilon_{(t-i)^2}$ at previous time points $t - i$. Together, these components contribute to estimating the evolving conditional variance and provide insights into the volatility dynamics of the time series data.

The dynamic conditional correlation model expands on the conventional correlation model by incorporating time-varying correlations. It postulates that the conditional correlation between two time series at a given time *t* is determined by the prior correlation and the historical shocks of the two series. Mathematically, it can be expressed as

$$R_t = \Omega + \sum(\alpha_i \times \varepsilon_{t-i} \times \varepsilon'_{t-i}) + \sum(\beta_i \times R_{(t-i)}), \quad (3)$$

where Ω represents a constant term, α_i denotes the model coefficients associated with the shocks ε_{t-i} and ε'_{t-i} at previous time points $t - i$, and β_i represents the model coefficients associated with the past correlations $R_{(t-i)}$. This formulation captures the evolving nature of correlations over time, providing insights into the dynamic relationship between the two time series (see, for example, Engle (2002)).

Cascade-correlation network[6]

Figure 5 presents the architecture known as the cascade-correlation network, which demonstrates remarkable capability in automatic node training and adaptive expansion during data analysis. This approach addresses a critical challenge in network design, namely determining the optimal size by iteratively adjusting the number of hidden layers and their connections. Unlike traditional network architectures that require a predetermined structure, the cascade-correlation network dynamically adapts its architecture to the complexity of the data, ensuring an optimal fit. The cascade-correlation network represents a prominent instance of feedforward neural networks and offers a valuable solution for analyzing datasets containing both quantitative and categorical variables. By maximizing the correlation among variables, this network model captures intricate relationships and uncovers patterns that might remain hidden in other approaches. Abdou et al. (2016) and Fahlman (1990) have extensively investigated the efficacy of the cascade-correlation

[6] It should be emphasized that the term cascade-correlation network refers to the "cascade-correlation *neural* network" (see Abdou et al., 2016).

network, highlighting its effectiveness within various domains. Their studies have emphasized its ability to overcome the challenges associated with determining the appropriate network size, thereby providing a flexible and adaptable framework for comprehensive data analysis. The integration of the cascade-correlation network as a complementary technique in our research serves to enhance the robustness and reliability of our findings. By utilizing this advanced neural network architecture, we can effectively leverage its adaptive nature and maximize the extraction of meaningful insights from complex datasets.

INSERT FIGURE 5

III. RESULTS AND DISCUSSION

A. Short-Term Volatility Contagion between Cryptocurrencies and Gold

When employing the DCC-GARCH model to analyze the data for the entire period, as presented in Table 2, no evidence of short-term volatility contagion between Bitcoin and gold is observed. This suggests the absence of shock transmission from the Bitcoin market to the gold market. Our findings align with those of Baur, Dimpfl, et al. (2018), who concluded that no relationship existed between Bitcoin and gold from July 2010 to June 2015. These results support existing literature indicating a weak relationship between Bitcoin and gold (see, for example, Giudici & Abu-Hashish, 2019 Gkillas et al., 2020, Mensi et al., 2023) and highlight the divergence in behavior between Bitcoin and gold (see, for example, Klein et al., 2018).

Analyzing the pre-COVID-19 data, as shown in Table 2, we find that volatility does not transfer from Bitcoin to gold in the short term. This result is consistent with previous research suggesting that Bitcoin cannot serve as a safe haven asset like gold (see, for example, Bouoiyour & Selmi, 2015; Long et al., 2021) and supports the notion of no relationship between Bitcoin and gold (see, for example, Baur, Dimpfl, et al., 2018; Ji et al., 2018; Kristoufek, 2015). However, this result contradicts literature suggesting a volatility transfer from Bitcoin to gold (see, for example, Bouri et al., 2018).

Regarding the COVID-19 period, our short-term results indicate volatility contagion between Bitcoin and gold, with volatility flowing from Bitcoin to gold. This implies the transmission of shocks from the Bitcoin market to the gold market. These findings are consistent with Bouri et al. (2018) who reported the transfer of volatility from Bitcoin to gold. It also flows in the same direction as the literature, which indicates the possibility of using Bitcoin as a safe haven like gold (see, for example, Brière et al., 2015; Kang et al., 2020). However, these results contradict those of Guesmi et al. (2019), who highlighted Bitcoin's potential for hedging risks associated with investing in gold.

INSERT TABLE 2

B. Short-Term Volatility Contagion between Cryptocurrencies and Stock Markets

Utilizing the DCC-GARCH model to analyze the data for the entire period, as displayed in Table 2, no evidence is found for short-term volatility contagion between Bitcoin and the six stock market indices. This indicates the absence of shock transmission from the Bitcoin market to these stock markets. Our results extend the findings of Ji et al. (2018), suggesting the isolation of the Bitcoin market from other financial instrument markets between July 2010 and January 2017. However, our results differ from those of Bouri et al. (2018), who indicated a relationship between Bitcoin returns and Chinese stock market returns. Additionally, our findings contradict the conclusions of Symitsi and Chalvatzis (2018), who identified the transmission of shocks from the Bitcoin market to stock markets.

Nonetheless, our results are consistent with literature that recommends using Bitcoin for stock portfolio diversification (see, for example, Baur, Hong, et al., 2018; Brière et al., 2015; Corbet et al., 2018; Feng et al., 2018; Kajtazi & Moro, 2019) in the short term. Furthermore, our results indicate short-term contagion between Bitcoin and only the Chinese stock market, signifying the transmission of shocks from the Bitcoin market to the Chinese stock market during COVID-19. These findings align with those of Bouri et al. (2018), who discovered a relationship between Bitcoin and the Chinese stock market. However, our results indicate no short-term contagion between Bitcoin and the stock markets of Japan, the US, the UK, Germany, and France, suggesting that Bitcoin shocks did not propagate to these markets during COVID-19. These findings are consistent with literature suggesting that Bitcoin can be used for equity portfolio diversification (see, for example, Baur, Hong, et al., 2018; Brière et al., 2015; Kang et al., 2020). We propose employing this diversification strategy within the specific context of these markets during times of crises and turbulence.

C. Long-Term Volatility Contagion between Cryptocurrencies and Gold

Our long-term results indicate the transmission of volatility between Bitcoin and gold, indicating the existence of volatility contagion between them throughout the study period. This finding contradicts the results of Guesmi et al. (2019), who proposed Bitcoin as a hedging tool against gold, but aligns with previous literature indicating a relationship between Bitcoin and gold (see, for example, Giudici & Abu-Hashish, 2019). Our investigation further reveals the transmission of volatility between Bitcoin and gold in the long term, supporting the existence of volatility contagion between them over the entire study period. The pre-COVID-19 long-term results exhibit volatility contagion from Bitcoin to gold, contradicting literature suggesting that no relationship exists between Bitcoin and gold (see, for example, Kristoufek, 2015) or that a weak relationship exists between the two (see, for example, Giudici & Abu-Hashish, 2019; Gkillas et al., 2020). The long-term results during COVID-19 align with the pre-COVID-19 period and the overall sample, indicating long-term contagion between Bitcoin and the gold market.

D. Long-Term Volatility Contagion between Cryptocurrencies and Stock Markets

Our investigation reveals the transmission of volatility between Bitcoin and the six stock market indices in the long term, indicating the existence of volatility contagion between them over the study period. The long-term results concerning pre-COVID-19 volatility contagion between Bitcoin and the six stock markets demonstrate its presence. These findings contradict literature that suggests using Bitcoin to hedge risks associated with investing in stocks (see, for example, Dyhrberg, 2016; Fang et al., 2019; Feng et al., 2018; Guesmi et al., 2019) and its potential for diversifying stock portfolios (see, for example, Baur, Hong, et al., 2018; Brière et al., 2015; Kang et al., 2020). The long-term results during COVID-19 mirror those observed pre-COVID-19 and throughout the entire sample, indicating long-term contagion between Bitcoin and the six stock markets before and during the pandemic.

E. Robustness analysis

To ensure accurate results, we performed an analysis using the cascade-correlation network model. Table 3 and Figure 6 suggest the transmission of contagion from Bitcoin to gold and the six stock markets throughout the entire period before and during COVID-19, as well as in the long term (see, for example, the R^2 values in Table 3). These results are consistent with our DCC-GARCH results. For the short term during COVID-19, the cascade-correlation network captures volatility contagion, first between Bitcoin and gold (with the lowest MAPE value of 2.104) and second between Bitcoin and the Japanese stock market (with the second-lowest MAPE value of 2.529). This result is confirmed by the heatmap (see Figure 6). It is worth mentioning that DCC-

GARCH failed to capture short-term contagion between Bitcoin and the Japanese stock market during COVID-19. However, it did capture short-term contagion between Bitcoin and the Chinese stock market at the 90% confidence level, which may not be generally accepted. Therefore, our proposed methodology suggests that using both the DCC-GARCH and the cascade-correlation network can be mutually supportive, as they capture *short-term* volatility contagion for the Chinese and the Japanese stock markets, respectively.

INSERT TABLE 3

INSERT FIGURE 6

F. Additional analysis using wavelet coherence model

To improve result accuracy and gain deeper insights into the direction, type, and strength of contagion, we utilized the wavelet coherence model, specifically the wavelet coherency model introduced by Grinsted et al. (2004). Conventional time series metrics offer insights solely at specific frequencies. In contrast, wavelet techniques can extract information across a spectrum of frequencies while preserving the temporal dimension (S. Kumar & Ajaz, 2019). The wavelet coherence model holds significant prominence among researchers for its extensive utilization in examining the intricate dynamics of contagion between markets (Aloui & Hkiri, 2014; Kirikkaleli & Güngör, 2021; Özdemir, 2022; Pal & Mitra, 2019; Szczygielski et al., 2023; Q. Xie et al., 2023). Employing this model, we generated heatmaps to monitor contagion dynamics among Bitcoin, gold, and the stock markets of Japan, the USA, the UK, China, Germany, and France over a specific period. These heatmaps provide valuable information regarding the strength, type, direction, and significance of contagion over time, thereby enabling us to examine contagion details both before and during the COVID-19 pandemic. The wavelet analysis decomposes the time series of variables into different scales based on time and reveals the changes that occur between these components at varying scales. The mother wavelet adeptly characterizes the intricate, high-frequency constituents of a time series. A wavelet mother function, denoted as $\psi(n)$, possessing a zero mean and normalized attributes, is expressed as follows:

$$\int_{-\infty}^{+\infty} \psi(n) dn = 0 \quad and \ \int_{-\infty}^{+\infty} |\psi(n)|^2 dn = 1$$

(4)

The wavelet mother function undergoes translation by the τ parameter and is subjected to dilation based on scale parameters, giving rise to "wavelet daughters" that collectively form a wavelet family utilized for filtering, as discussed in the study by Mestre (2021). These "wavelet daughters," as described by Shah et al. (2018), manifest as smaller waveforms when applied to the return series n at a given scale k. This phenomenon is exemplified by the mathematical expression

$$\psi_{\tau,k}(n) = \frac{1}{\sqrt{k}} \psi\left(\frac{n-\tau}{k}\right), \tag{5}$$

where $\frac{1}{\sqrt{k}}$ serves as a normalization factor, k represents the scale, and τ denotes the time position. Previous empirical studies have employed various types of wavelets for time series decomposition. In our research, we use the Morlet wavelet, known for its outstanding capabilities in examining time series data related to Bitcoin, gold, and stock markets, as substantiated by empirical evidence presented in the work of Bouri et al. (2020). Furthermore, it is acknowledged for achieving an optimal equilibrium between temporal and frequency localization, as underscored by the research of Aguiar-Conraria and Soares (2011). Grinsted et al. (2004) indicated that the Morlet wavelet's Fourier period nearly equals the scale used and can be expressed as

$$\psi^M(n) = \frac{1}{\pi^{1/4}} e^{i\omega_0 n} e^{-n^2/2}, \quad (6)$$

where ω_0 represents the wavelet's central frequency. The discrete-time series continuous wavelet transforms w_j are computed as

$$w_j(\tau, k) = \int_{-\infty}^{+\infty} x(n)\psi^*_{\tau,k}(n)dn = \frac{1}{\sqrt{k}}\int_{-\infty}^{+\infty} x(n)\psi^*\left(\frac{n-\tau}{k}\right)dn, \quad (7)$$

where $*$ denotes the complex conjugate. The variance is determined by

$$\|x\|^2 = \frac{1}{C_\psi} \int_0^\infty \left[\int_{-\infty}^{+\infty} \left|W_j(\tau, k)^2\right| d\tau\right] \frac{dk}{k^2}, \quad (8)$$

The cross-wavelet power, denoted $\left|W_j(\tau, k)^2\right|$, which delineates regions of synchronized behavior between two time series, is formally described in the work of Torrence and Compo (1998). In their formulation, the cross-wavelet power is computed as the product of the continuous wavelet transforms of the two time series, namely $j(n)$ and $l(n)$, represented by $W_j(\tau, k)$ and $W_l(\tau, k)$, respectively:

$$W_{jl}(\tau, k) = W_{jl}(\tau, k) \,.\, W_l^*(\tau, k), \quad (9)$$

In the time-frequency domain, the cross-wavelet power reveals the high common power between the series. The squared coherence of the wavelet is given by

$$R^2(\tau, K) = \frac{\left|K\left(k^{-1} jl(\tau, k)\right)\right|^2}{K\left(k^{-1}\left|K\left(W_j(\tau, k)\right)\right|^2\right) . K(k^{-1}|W_l(\tau, k)|^2)}, \quad (10)$$

where $K(.)$ represents the smoothing operator, and R^2 denotes the wavelet squared coherency. The phase difference is calculated as

$$\phi_{jl} = \tan^{-1}\frac{\Im\left\{W_{jl}(\tau, K)\right\}}{\Re\left\{W_{jl}(\tau, K)\right\}}, \phi_{jl} \in [-\pi, \pi], \quad (11)$$

where $\Re$ and $\Im$ represent the smooth power spectrum real part and imaginary, respectively.

The data smoothing procedures, as delineated in Equations 10 and 11, entail the application of a weighted running average, often referred to as convolution, along both temporal and scale dimensions. It is noteworthy to acknowledge that, akin to Fourier coherency, wavelet coherency relies on the utilization of a smoothing function. Nonetheless, the Morlet wavelet function, characterized by its intrinsic properties, naturally prescribes the width of this smoothing function across both temporal and Fourier domains. Temporal smoothing is accomplished through the utilization of a filter constructed from the absolute values of the wavelet function at each scale, with meticulous normalization to ensure a total weight sum of unity (Torrence & Webster, 1999). This method confers upon us the analytical capability to discern and scrutinize instances of cross-market contagion within our model, offering a convenient and rigorous means of validating our research findings.

The wavelet coherence model was employed to generate heatmaps, as presented in Figure 7. The horizontal axis delineates the timeline in years, while the vertical axis measures time in days, signifying the time horizon. Longer time horizons are indicated by lower positions along the vertical axis, denoting a more extended period. Time intervals of approximately 1 to 16 days are classified as short-term, whereas values exceeding 16 days pertain to the long term. Each heatmap provides a visual representation of the intricate interplay between Bitcoin and a distinct variable, such as gold and stock markets, as explicitly designated in the heading of each heatmap. Upward-pointing arrows (↑) and diagonal arrows (↘ and ↖) serve as indicators of Bitcoin's pivotal role as the leading influencer in contagion dynamics between itself and the specific variable under scrutiny. This implies that contagion transmission is predominantly instigated by Bitcoin affecting the other variable. In contrast, downward-pointing arrows (↓) and reverse diagonal arrows (↗ and ↙) imply that the other variable, whether it be gold or the stock markets, assumes the primary role in driving the contagion relationship between itself and Bitcoin. In such instances, the contagion predominantly originates from these variables, impacting Bitcoin. Right-pointing arrows demonstrate a positive relationship between Bitcoin and gold or stock markets, whereas left-pointing arrows indicate an inverse relationship (Elamer et al., 2022; Ibrahim et al., 2022). The solid black lines within the heatmaps demarcate statistically significant relationships at a confidence level of 5%. Cooler colorations, represented by various shades of blue, denote a less pronounced contagion effect between the variables, whereas warmer color gradients, predominantly depicted in shades of red, serve as indicators of a more pronounced and robust contagion dynamic (Bhuiyan et al., 2023). Based on the objectives of our study, our results can be divided into four layers.

First layer: the short-term volatility contagion between cryptocurrencies and gold:

Figure 7 provides evidence of short-term contagion at a frequency of 16 or less between Bitcoin and gold during the COVID-19 period. This contagion exhibits a higher frequency and broader impact than during the prepandemic period. Furthermore, the figure suggests that initially, the contagion flowed from gold to Bitcoin at the onset of the pandemic, whereas during the subsequent period, a synchronous relationship was observed between the two variables. These findings shed light on the dynamic nature of contagion between Bitcoin and gold, emphasizing the significance of the COVID-19 context in shaping the direction of contagion. One potential rationale for this conduct may be attributed to apprehension experienced by market participants stemming from the uncertainty surrounding COVID-19 and its economic ramifications. This apprehension led them to turn to gold as a safe haven investment. Additionally, Bitcoin garnered attention, particularly after the surge in gold prices, as some view it as the digital counterpart to gold. This result exhibits strong concurrence with the outcomes derived from employing the DCC-GARCH model and the cascade-correlation network model.

Second layer: the short-term volatility contagion between cryptocurrencies and stock markets:

Figure 7 suggests the presence of short-term contagion occurring at a frequency of 16 or lower between Bitcoin and the stock markets of Japan, China, and the United States. These results bear similarities to those proposed by the DCC-GARCH model and the cascade-correlation network model, with the outcomes of the cascade-correlation network model exhibiting a stronger resemblance. Specifically, the cascade-correlation network model successfully captures contagion between Bitcoin and the Japanese stock market, whereas the DCC-GARCH model fails to do so. Additionally, Figure 7 indicates that contagion between Bitcoin and these markets follows a positive relationship. These findings potentially indicate a harmonized perspective among participants engaged in both the Bitcoin market and the stock markets of the United States, Japan, and China. It is conceivable that these market participants hold investments in both domains, notably due to the widespread availability of brokerage firms facilitating CFDs for these financial instruments, thereby catering to traders with diverse backgrounds. Conversely, discernible distinctions emerge in the viewpoints of those involved in the stock markets of Germany, the United Kingdom, and France when juxtaposed with participants within the Bitcoin market. This divergence hints at nuanced psychological responses to price dynamics, proposing the utility of cryptocurrencies as a strategic diversification tool within these nations. In addition, one potential explanation for the contagion between Bitcoin and the stock markets of the United States, China, and Japan could be attributed to the presence of the two largest cryptocurrency exchanges, namely Coinbase (a US-based exchange) and Binance (originally founded in China and later relocating its headquarters to Singapore).

Third layer: the long-term volatility contagion between cryptocurrencies and gold:

Figure 7 suggests a long-term contagion relationship between Bitcoin and gold before and after COVID-19, occurring at frequencies greater than 16. This contagion intensified during the COVID-19 pandemic. Furthermore, it indicates that contagion before COVID-19 was synchronous, with the direction shifting from Bitcoin to gold during the pandemic. These findings exhibit strong similarities to those proposed by the DCC-GARCH model and the cascade-correlation network model. Additionally, Figure 7 indicates a positive relationship in contagion dynamics between Bitcoin and gold before and after COVID-19, except for a brief period in early 2015 when it exhibited a negative relationship.

Fourth layer: the long-term volatility contagion between cryptocurrencies and stock markets:

Based on Figure 7, empirical evidence supports a long-term contagion relationship between Bitcoin and the stock markets of Japan, the United States, the United Kingdom, China, Germany, and France. Among these markets, the United States, Japan, France, and Germany exhibit the most pronounced contagion levels for the entire duration of the study. Specifically, within the pandemic context, the observed contagion levels were most pronounced in France, followed by Japan, Germany, and the United States. These findings align with insights presented by Bouri et al. (2023) that imply the prospective applicability of Bitcoin in forecasting US stock market performance. Conversely, the stock market of China demonstrates the lowest long-term contagion among the examined markets. This divergence may be attributed to China's implementation of stringent measures, including the complete prohibition of cryptocurrency trading exchanges, that took effect in September 2017 (Chen & Liu, 2022).

Based on the analysis presented in Figure 7, the heatmap indicates that contagion in the stock markets of Japan and Germany during the pandemic flowed from stock markets to Bitcoin. Conversely, during the trade war between the United States and China, contagion flowed from Bitcoin to the stock market. These findings imply that the reaction of Bitcoin to the trade war was quicker than the response of these markets, whereas the response of these markets to the pandemic was faster than that of Bitcoin. During both the prepandemic and the pandemic periods, simultaneous contagion was observed between the stock market in the United Kingdom and Bitcoin. In China, the direction of contagion was consistently from Bitcoin to the stock market, both before and during the pandemic. In contrast, the contagion exhibited a reverse pattern, flowing from the UK stock market to Bitcoin. In the case of the United States, the direction of contagion was characterized by volatility before the pandemic but became synchronous during the pandemic.

The findings indicate a notable long-term contagion relationship between Bitcoin and these markets, characterized by a positive association before and during the pandemic. However, intermittent periods of an inverse relationship lasting no longer than 4 months were observed in each market from 2014 to 2018.

There is a notable resemblance between the outcomes derived from the wavelet coherence model and those put forth by the DCC-GARCH and cascade-correlation network models. This resemblance indicates the accuracy of our findings. Additionally, our novel findings highlight the potential application of machine learning, specifically the cascade-correlation network model, in assessing contagion among markets. This model successfully captured outcomes that the GARCH model was unable to grasp and exhibited a capability to reproduce results similar to those obtained from the wavelet coherence model.

IV. CONCLUSION AND AREAS FOR FUTURE RESEARCH

In recent times, the world has become increasingly interconnected through economic and political links. The speed of transmission of news and events across the world has enabled the possibility of contagion—economic, health-related, or otherwise—from one country to another. Furthermore, the emergence of new, previously unavailable tools may potentially affect the global community as a whole. While these tools present opportunities, they also pose significant risks that must be identified and addressed. The outbreak of the COVID-19 pandemic has further highlighted the vulnerability of economies and financial markets to unforeseen shocks. Against this backdrop, our investigation focuses on the transmission of market volatility contagion from cryptocurrency, a relatively new tool, to traditional markets such as gold and stock markets. Specifically, we examine the extent of contagion from the Bitcoin market to the Japanese, US, UK, Chinese, German, and

French stock markets. Using a dataset spanning from January 2, 2011, to June 2, 2022, and employing both DCC-GARCH and cascade-correlation network models as mutually supportive statistical techniques, we provide insights into the nature and extent of market contagion in the face of economic shocks such as the COVID-19 pandemic.

The results suggest no evidence of short-term volatilization between Bitcoin and the six stock markets pre-COVID-19. This finding contradicts that suggested by Bouri et al. (2018) regarding the existence of a relationship between Bitcoin and the Chinese stock market and what was found by Symitsi and Chalvatzis (2018)—shock transmissions from the Bitcoin market to the stock markets. However, our study reveals the presence of long-term volatility contagion between Bitcoin and gold in general both before and during COVID-19. Additionally, we found evidence of short-term volatilization contagion between Bitcoin and gold during COVID-19. This implies the transmission of shocks between these markets during periods of turmoil and uncertainty.

Furthermore, our findings indicate the existence of long-term contagion, both before and during COVID-19, between Bitcoin and the stock markets of Japan, the USA, the UK, China, Germany, and France. Moreover, we found evidence of short-term volatility contagion during COVID-19 between Bitcoin and the Chinese stock market based on DCC-GARCH results and between Bitcoin and the Japanese stock market based on cascade-correlation network results. This suggests the transmission of market shocks from Bitcoin to both the Chinese and the Japanese stock markets during periods of uncertainty and confusion.

The contagion identified in our findings can be elucidated, in alignment with the interpretation proposed by Jokipii and Lucey (2007), through the lens of behavioral theories influencing investor actions. A noteworthy segment of financial market participants possesses investments across the gold market, Bitcoin, as well as the stock markets in the United States, China, and Japan. With the onset of the COVID-19 pandemic, these investors opted to divest from their stock market holdings, leading to a decline in stock prices. Seeking a hedge against uncertainty, they turned to gold as a safe haven, triggering a surge in its value. It is crucial to highlight that the involvement of both American and Chinese cryptocurrency exchanges played a pivotal role in this context. A considerable portion of these market participants regard Bitcoin as a digital equivalent of gold. Consequently, they shifted their investments toward Bitcoin following the surge in gold prices. Subsequently, as stock prices plummeted to historically low levels, and these participants realized substantial profits in the gold and Bitcoin markets, they redirected their investments back into the stock market. These investment shifts, underpinned by investor behavior, engendered contagion among these diverse markets.

Our study has practical implications for policymakers, investors, and financial institutions by shedding light on the potential transmission of Bitcoin's volatility contagion to traditional markets. Policymakers in the stock markets studied can use our results to develop measures to prevent the spread of contagion from Bitcoin to their local markets. Investors can also benefit from our study by taking steps to manage the risks associated with contagion from Bitcoin to the stock markets, especially for those who use gold or Bitcoin as a safe haven. Hedge funds and mutual funds can use our study to improve their risk management strategies.

Future research could explore contagion between cryptocurrencies and other markets, such as energy markets or stock markets in oil-exporting or oil-importing countries. Additionally, using other advanced Machine Learning techniques, such as fuzzy algorithms, gene expression programming, and proportional hazard models, can further enhance the understanding of contagion dynamics between Bitcoin and traditional markets. Overall, our findings provide valuable insights into the potential risks associated with Bitcoin volatility contagion and suggest the need for further research in this field. Moreover, a comprehensive analysis of the variables contributing to intermarket contagion can encompass a broad spectrum of factors spanning psychological, economic, legal, and technological dimensions. The insights derived from such an extensive exploration may potentially offer substantial benefits to policymakers, investors, investment funds, and risk management entities.

List of abbreviations

Abbreviation	Definition
BTC	Bitcoin
Nikkei 225	A price-weighted equity index, which consists of 225 stocks in the Prime Market of the Tokyo Stock Exchange
SPX 500	A market-capitalization-weighted index of 500 leading publicly traded companies in the U.S.
FTSE 100	A market-capitalization index of the 100 largest (by market capitalization) companies listed on the London Stock Exchange.
FTSE China A50	**A** benchmark of the Chinese domestic A-shares market. It measures the performance of the 50 largest A-shares companies traded on Chinese stock markets
DAX	A stock index that represents 40 of the largest and most liquid German companies that trade on the Frankfurt Exchange
CAC 40	The French stock market index that tracks the 40 largest French stocks based on the Euronext Paris market capitalization
CFDs	*Contracts for differences*
R^2	Proportion of variance explained by model
CV	Coefficient of variation
NMSE	Normalized mean square error
Panel A	The entire study period
Panel B	Pre-COVID-19 sub-period
Panel C	During-COVID-19 sub-period
XAU	Gold
JPN	Nikkei 225
SPX	SPX 500 or S&P 500
UK	FTSE 100
CHN	China A50
DEU	DAX
CAC	CAC 40

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TABLES

Table 1: Summary statistics of daily return series

	BTC	XAU	JPN	SPX	UK	CHN	DEU	CAC
Panel A: Descriptive statistics								
Minimum	-0.49373	-0.09572	-0.11723	-0.11275	-0.1133	-0.10919	-0.1305	-0.13098
Maximum	0.59327	0.04690	0.07671	0.09657	0.08824	0.09691	0.10414	0.08056
1. Quartile	-0.01656	-0.00468	-0.00636	-0.0036	-0.00441	-0.00652	-0.0052	-0.00560
3. Quartile	0.02459	0.00515	0.00779	0.00555	0.0052	0.00671	0.00652	0.00640
Mean	0.00389	0.00009	0.00033	0.00039	0.00007	0.00012	0.00024	0.00017
Median	0.00259	0.00039	0.00058	0.000	0.00014	0.000	0.00056	0.00044
Variance	0.00337	0.00009	0.00018	0.00011	0.00011	0.00021	0.00016	0.00016
Stdev	0.05805	0.00961	0.01346	0.01082	0.01087	0.01478	0.01282	0.01275
Skewness	0.07793	-0.64260	-0.59478	-0.73344	-1.07615	-0.26628	-0.4879	-0.63837
Kurtosis	12.13382	6.34121	6.37933	13.85575	15.24656	6.1548	8.13446	8.231883

Note: Our data consists of 2,958 daily observations from January 2, 2011, to June 2, 2022, and divided into two sub-samples. The first sub-sample covers the period from January 2, 2011, to February 23, 2020, which is pre-COVID-19. The second sub-sample covers the period from February 24, 2020, to June 2, 2022, which is during COVID-19. This Table presents daily return summary statistics for Bitcoin (BTC), gold (XAU), and six international stock market indices CFDs namely Nikkei 225 (JPN), S&P 500 (SPX), FTSE 100 (UK), FTSE China A50 (CHN), DAX (DEU), CAC40 (CAC). ADF and PP are the statistics of the augmented Dickey-Fuller and Philip-Perron unit root tests, respectively. This Table shows that Bitcoin reached the lowest daily return (i.e., -0.49373) and the highest daily return (i.e., 0.59327) among other returns, which is the highest in average returns and volatility as evidenced by the Mean, Median, and Variance figures above.

Table 2: Estimation results for DCC-GARCH model

	XAU	JPN	SPX	UK	CHN	DEU	CAC
Panel A: The entire period							
omega	0.004401	0.008224	0.000961	0.002213	0.004594	0.009263	0.001036
alpha1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
beta1	0.995525	0.991995	0.999000	0.997757	0.995351	0.990968	0.999000
dcca1	0.000172	0.000671	0.003893	0.000000	0.000000	0.005089	0.004872
dccb1	0.973548***	0.994093***	0.978700***	0.915061***	0.925486***	0.971512***	0.983465***
Panel B: Pre COVID-19							
omega	0.000001	0.000007	0.000005	0.000005	0.000001	0.000002	0.000004
alpha1	0.039868	0.156515	0.236659	0.186385	0.057204	0.075542	0.115374
beta1	0.951317	0.812143	0.726104	0.764684	0.939533	0.907207	0.862554
dcca1	0.010173	0.003083	0.003784	0.764684	0.001801	0.005254	0.002650
dccb1	0.942313***	0.987478***	0.975360***	0.982598***	0.987014***	0.974355***	0.979150***
Panel C: During COVID-19							
omega	0.000009	0.000014	0.000007	0.000007	0.000038	0.000009	0.000011
alpha1	0.102585	0.134884	0.211719	0.202472	0.208013	0.176419	0.177001
beta1	0.812815	0.787048	0.751386	0.755889	0.634885	0.790760	0.777446
dcca1	0.015464**	0.009739	0.007577	0.008072	0.015343*	0.024397	0.013131
dccb1	0.976834***	0.962922***	0.979842***	0.977587***	0.973207***	0.663379***	0.935435***

Notes: Our data consists of 2,958 daily observations from January 2, 2011, to June 2, 2022, and divided into two sub-samples. The first sub-sample covers the period from January 2, 2011, to February 23, 2020, which is pre-COVID-19. The second sub-sample covers the period from February 24, 2020, to June 2, 2022, which is during COVID-19. *** indicate statistical significance at the 1% level. ** indicate statistical significance at the 5% level. * indicate statistical significance at the 10% level. This Table shows a long-term volatility contagion between Bitcoin, gold, and the six stock markets during the entire study period (across the three Panels above). There is two short-term volatility contagion between Bitcoin and gold: and between Bitcoin and the Chinese stock market during COVID-19 (i.e., Panel C).

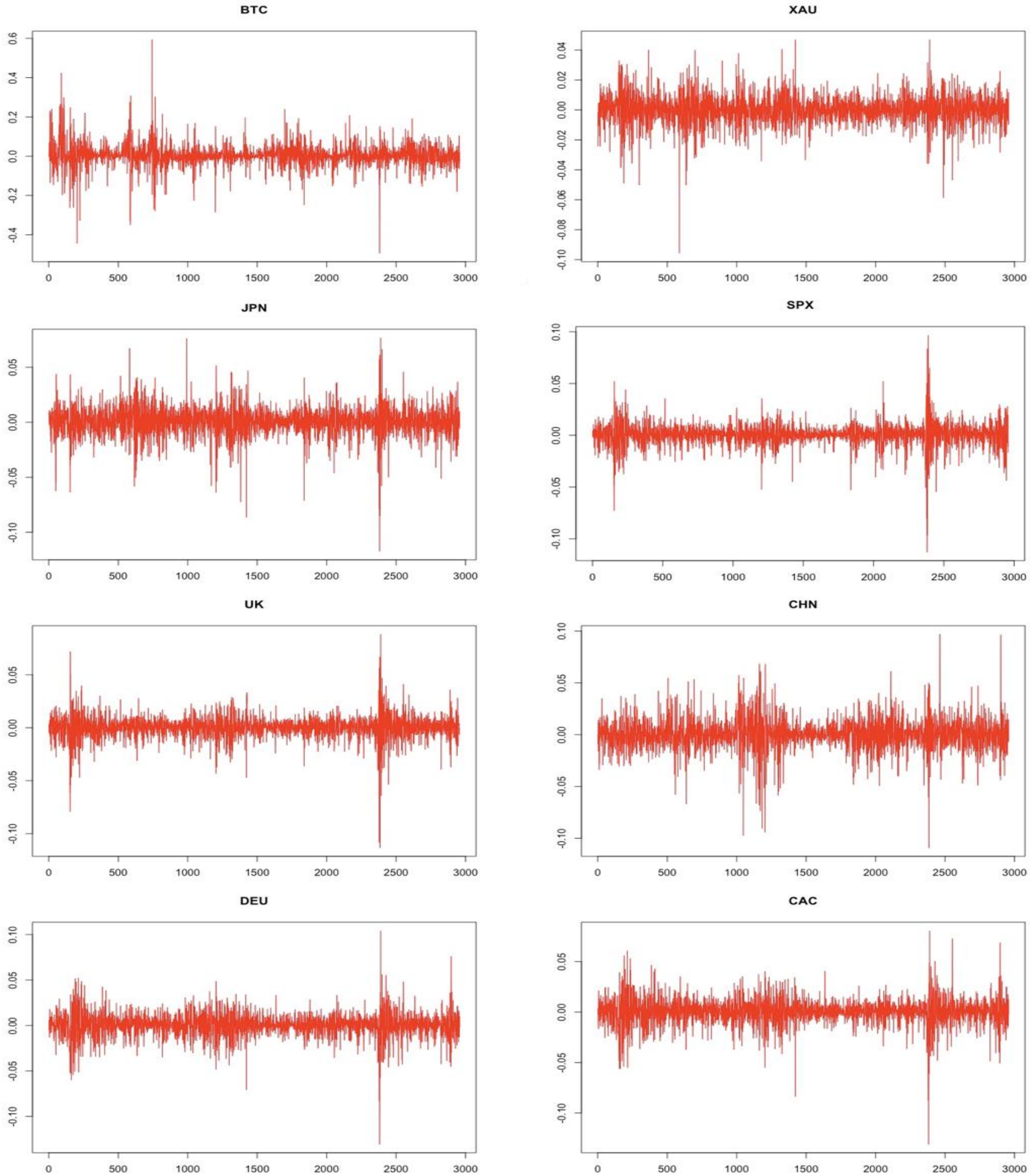
Table 3. Cascade-Correlation network results

	Panel A: The entire sample							*Panel B: Pre-COVID-19*							*Panel C: During-COVID-19*						
	XAU	**JPN**	**SPX**	**UK**	**CHN**	**DEU**	**CAC**	**XAU**	**JPN**	**SPX**	**UK**	**CHN**	**DEU**	**CAC**	**XAU**	**JPN**	**SPX**	**UK**	**CHN**	**DEU**	**CAC**
Model Parameters																					
Input Layer																					
Number of neurons	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Hidden Layer																					
Number of neurons	25	26	27	16	30	22	15	19	20	24	18	18	23	18	10	7	8	6	8	11	6
Sigmoid neurons	3	5	4	3	2	4	1	4	2	6	5	3	3	2	3	0	1	1	3	1	1
Gaussian neurons	22	21	23	13	28	18	14	15	18	18	13	15	20	16	7	7	7	5	5	10	5
Minimum weight	-9893	-3426	-929	-3346	-512	-3863	-3567	-1225	-1137	-484	-5702	-692	-1292	-30	-134	-37	-20	-2505	-781	-175	-288
Maximum weight	437	660	118	34	152	114	9.247	97453	11767	1151	394	1298	23876	1345	1215	18	268	11	247	48	22
Output Layer																					
Number of neurons	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Minimum weight	-0.395	-0.330	-0.333	-0.265	-0.299	-0.282	-0.312	-0.208	-0.403	-0.196	-0.424	-0.264	-0.407	-0.154	-0.400	-0.445	-0.066	-0.259	-0.174	-0.427	-0.075
Maximum weight	0.62	0.414	0.444	0.666	0.281	0.393	0.598	0.381	0.473	0.381	0.385	0.394	0.459	0.574	0.612	0.581	0.523	0.514	0.35	0.424	0.666
Analysis of Variance																					
R^2	0.836	0.969	0.970	0.674	0.891	0.943	0.887	0.863	0.957	0.955	0.890	0.792	0.940	0.924	0.712	0.935	0.900	0.840	0.611	0.86	0.855
CV	0.068	0.056	0.065	0.055	0.092	0.059	0.067	0.049	0.059	0.057	0.032	0.104	0.054	0.047	0.026	0.032	0.049	0.036	0.077	0.044	0.056
NMSE	0.163	0.030	0.029	0.325	0.108	0.056	0.112	0.136	0.042	0.044	0.109	0.207	0.059	0.075	0.287	0.064	0.099	0.159	0.488	0.13	0.144
MAPE	4.887	4.436	4.828	4.042	7.420	4.494	5.478	3.631	4.874	4.243	2.568	8.741	4.317	3.702	2.104	2.529	3.601	2.873	5.419	3.932	4.260

Note: Our data consists of 2,958 daily observations from January 2, 2011, to June 2, 2022, and divided into two sub-samples. The first sub-sample covers the period from January 2, 2011, to February 23, 2020, which is pre-COVID-19. The second sub-sample covers the period from February 24, 2020, to June 2, 2022, which is during COVID-19. This Table shows Cascade-Correlation, network models. This Table shows that gold (XAU) and the Japanese stock market (JPN) have the lowest MAPE values of 2.104 and 2.529, respectively which indicate a short-term volatility contagion between Bitcoin and both gold and the stock market of Japan.

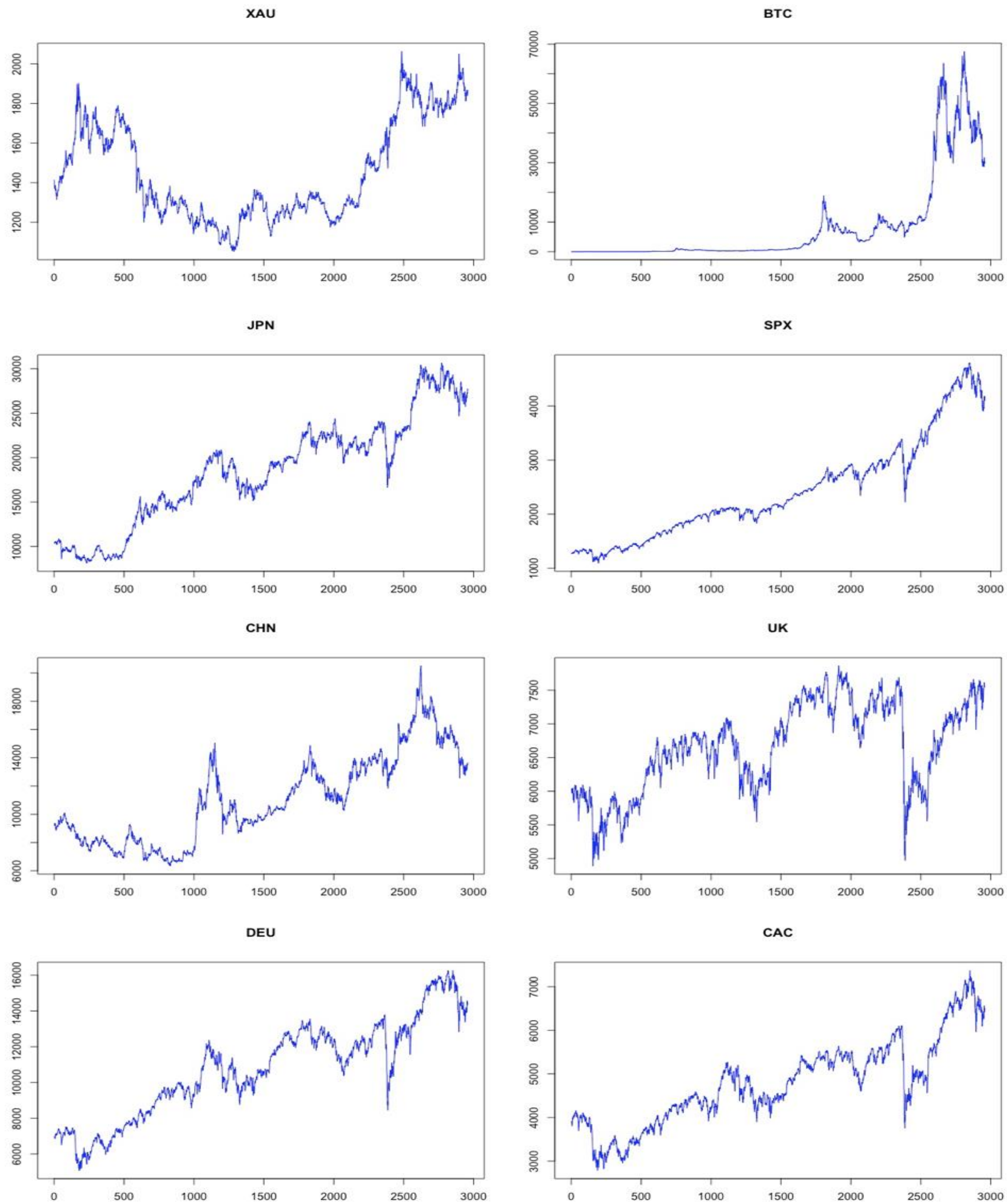
FIGURES

Figure 1. Returns of Bitcoin, gold, and the six international stock indices CFDs.



Note: BTC: Bitcoin, XAU: Gold, JPN: Nikkei 225, SPX: S&P 500, UK: FTSE 100, CHN: China A50, DEU: DAX and CAC: CAC 40. In this Figure, the horizontal axis shows the number of days, and the vertical axis shows returns. This Figure suggests a similarity in the volatility between Bitcoin, gold, and the six stock market indices from January 2, 2011, to June 2, 202,2, and, in particular, with the COVID-19 pandemic (e.g., between 2000 and 2500 days on the horizontal line).

Figure 2. Prices and values of Bitcoin, gold, and the six international stock indices CFDs.

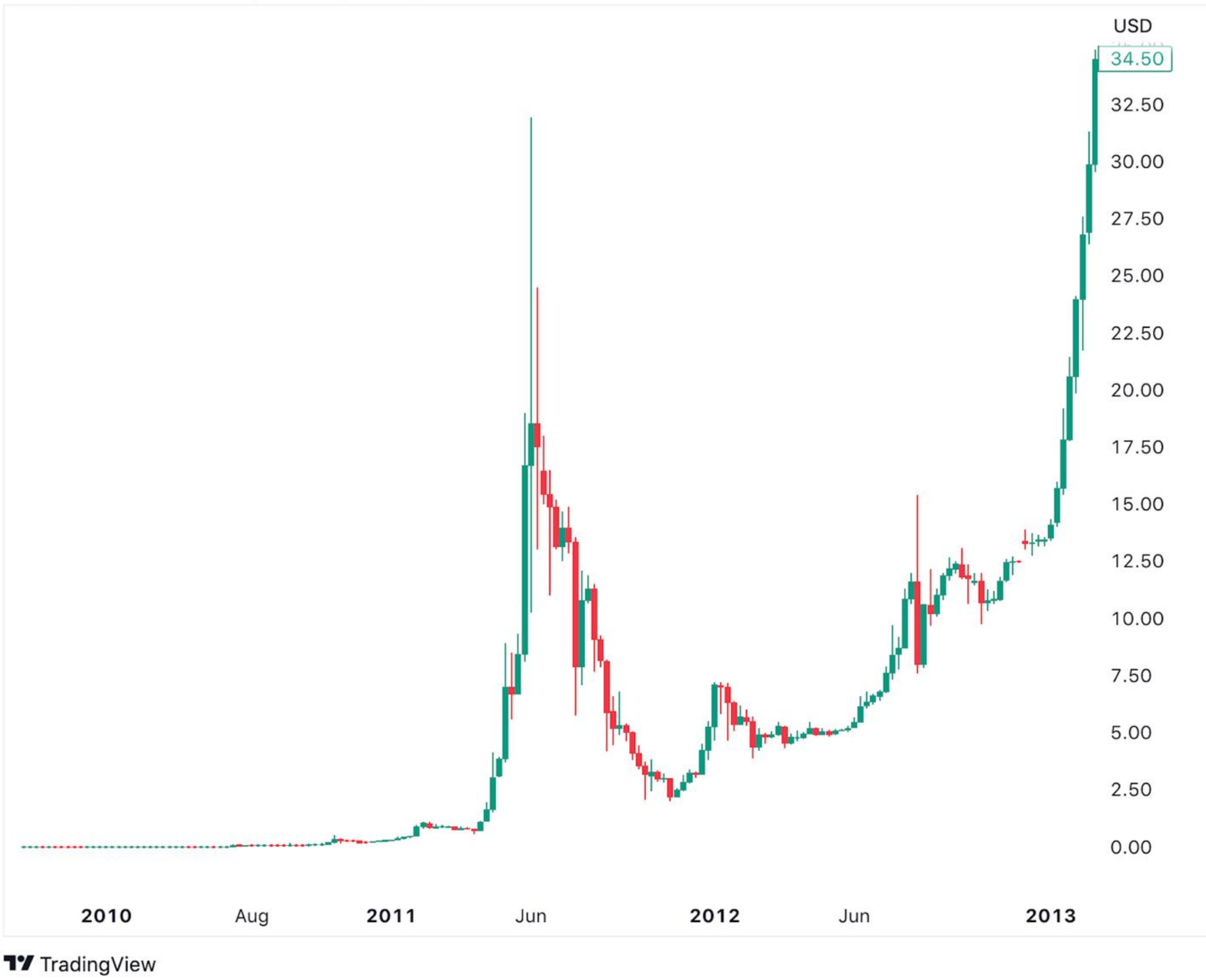


Note: BTC: Bitcoin, XAU: Gold, JPN: Nikkei 225, SPX: S&P 500, UK: FTSE 100, CHN: China A50, DEU: DAX and CAC: CAC 40. In this Figure, the horizontal axis shows the number of days, and the vertical axis shows values of stock market indices, gold prices, and Bitcoin prices.. This Figure suggests a similarity in the volatility between

Bitcoin, gold, and the six stock market indices from January 2, 2011, to June 2, 202,2, and, in particular, with the COVID-19 pandemic (e.g., between 2000 and 2500 days on the horizontal line).

Figure 3. Bitcoin Japanese candlestick chart

Source: TradingView[7]



Note: This Figure shows the stability of the Bitcoin price and the absence of noticeable volatility before the beginning of 2011. However, it is notable that the volatility started around the second quartile of 2011 (as shown above) and has continued throughout the study period up to 2022 (see, for example, https://www.tradingview.com).

[7] See https://www.tradingview.com

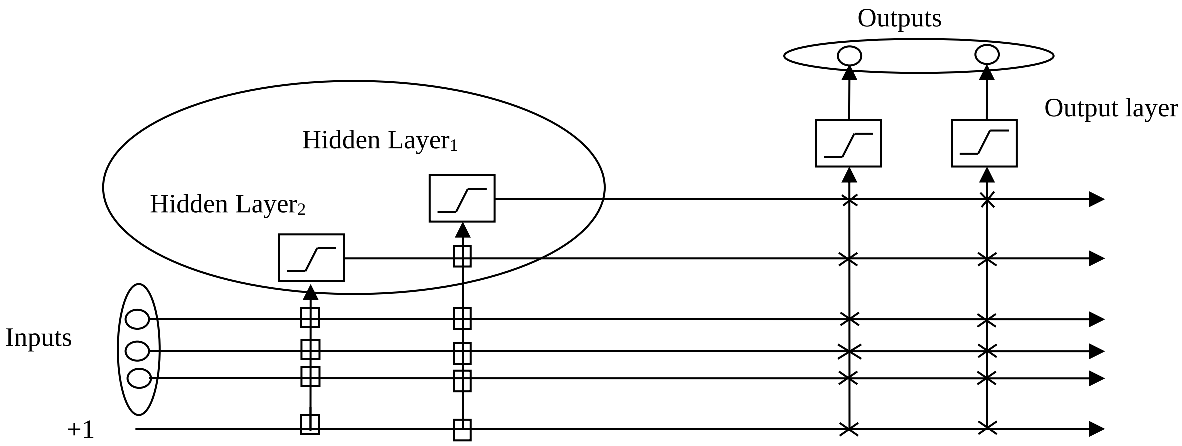
Figure 4. Study variables chart

Source: TradingView[8]

Note: BTC: Bitcoin, XAUUSD: Gold, JPN225: Nikkei 225, SPX: S&P 500, UK100GBP: FTSE 100, CHN50: China A50 and DEU: DAX. This Figure shows the beginning of the interaction between Bitcoin, gold, and the six stock market indices and the news on COVID-19 on February 24, 2020, where sharp collapses start with the lowest values between March and April 2020. Clearly, this Figure shows the collapse in Bitcoin and various stock indices compared to the rise in gold prices (the dark green line in the top right corner).

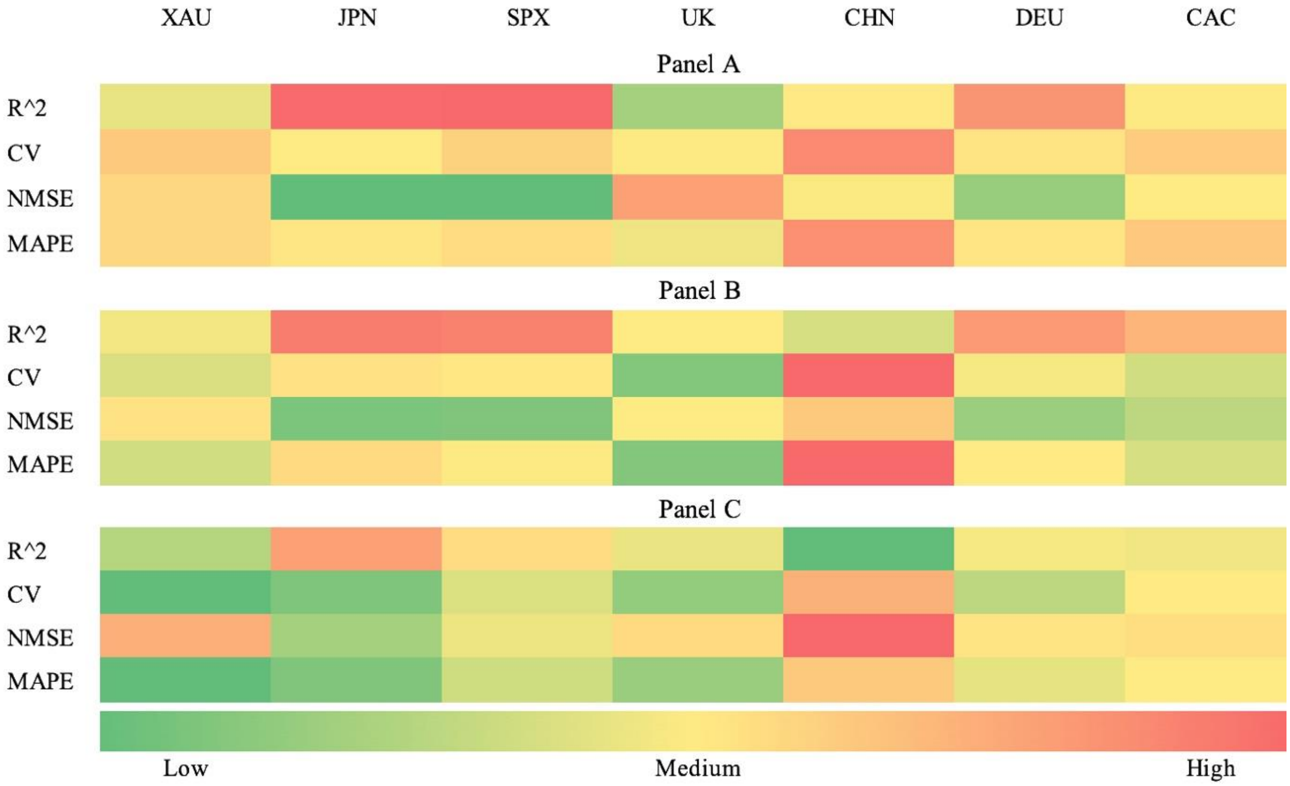
[8] See https://www.tradingview.com

Figure 5: Architecture of a Cascade Correlation network



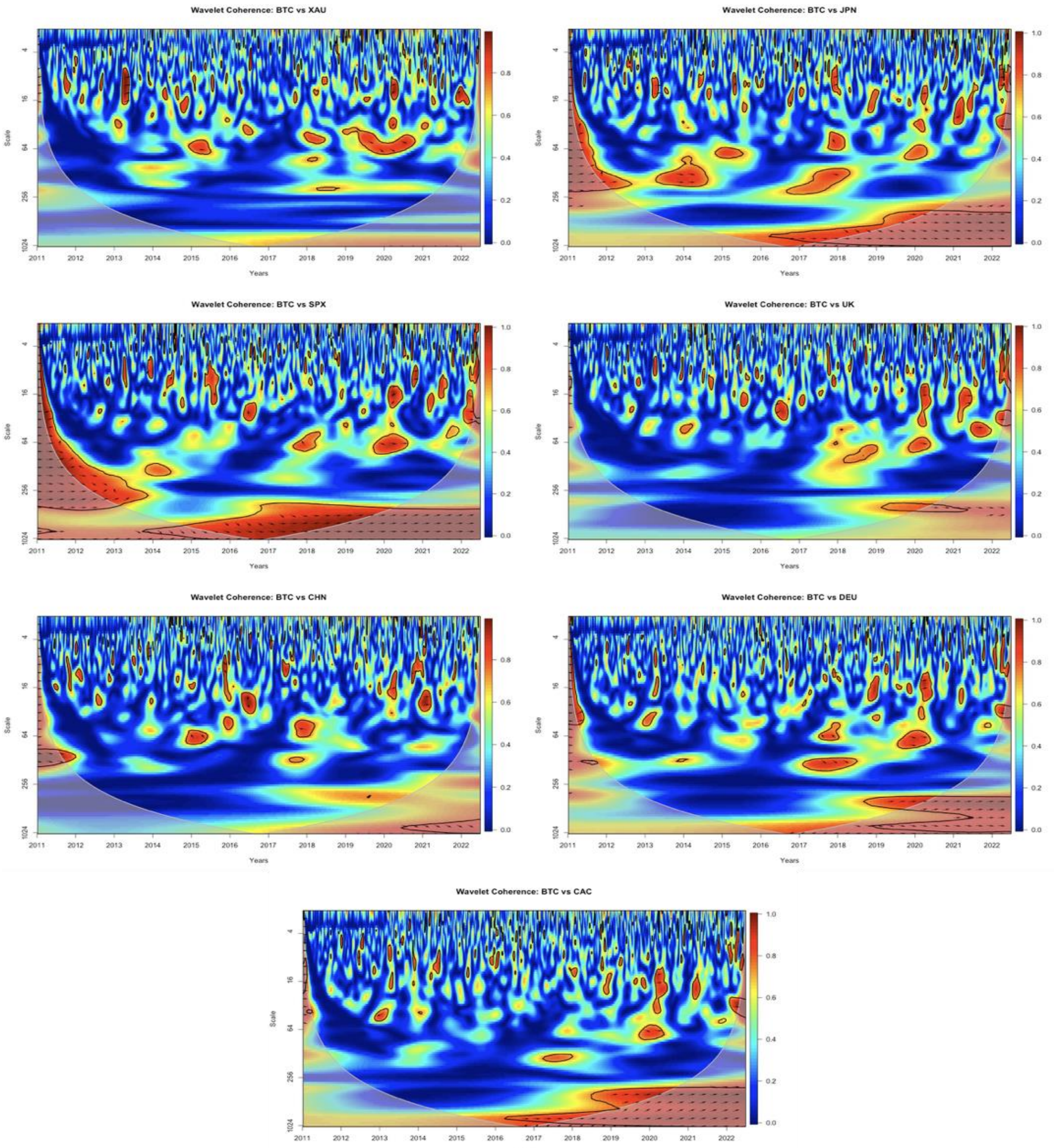
Note: As shown in Figure 5, a Cascade Correlation network comprises an input layer, one or more hidden layers, and an output layer. The cascade architecture is characterized by its adaptive growth, where hidden neurons are introduced sequentially as the training progresses. Unlike traditional neural networks, where all hidden neurons are preset at the onset of training, in Cascade Correlation networks, once a neuron is added to the hidden layer, its incoming weights become frozen, ensuring that its pattern of activity is not modified in subsequent iterations. This dynamic architecture aids in the enhancement of the network's capability and adaptability. The second foundational principle revolves around the learning process. When introducing a new neuron to the hidden layer, the training algorithm specifically aims to maximize the correlation between the output of this newly added component and the residual error of the network. This approach ensures that each added neuron makes a significant contribution towards correcting the overall network error, leading to efficient and effective training. This combination of dynamic architecture and specialized learning makes the Cascade Correlation network a powerful tool for various tasks. Source: Abdou, et al. (2016), pp. 91-92, Modified.

Figure 6. Comparison heat map for Cascade-Correlation network analysis of variance results



Note: R^2: Proportion of variance explained by the model, CV: Coefficient of variation, NMSE: Normalized mean square error, MAPE: Mean Absolute Percentage Error, Panel A: The entire study period, Panel B: pre-COVID-19, Panel C: during-COVID-19, XAU: gold, JPN: Nikkei 225, SPX: S&P 500, UK: FTSE 100, CHN: China A50, DEU: DAX and CAC: CAC 40. The warmer the color indicates a stronger relationship, which means contagion in the long term, while the cooler the color indicates a stronger relationship in the short term. It is clear from this Figure that the results of DCC-GARCH model are confirmed, which indicates a long-term volatility contagion between Bitcoin, gold, and the six stock markets. While there is a short-term contagion during COVID-19 between Bitcoin and gold, on one side; and between Bitcoin and the Japanese stock market on the other side (the darker green color of MAPE in the lower left corner), which is in line with the Cascade Correlation network results presented in Table 3.

Figure 7. Wavelet coherence heat maps



Note: BTC: Bitcoin, XAU: Gold, JPN: Nikkei 225, SPX: S&P 500, UK: FTSE 100, CHN: China A50, DEU: DAX and CAC: CAC 40. In this Figure, the horizontal axis delineates the timeline by years, while the vertical axis measures time in days, signifying the time horizon. Longer time horizons are indicated by lower positions along the vertical axis, denoting a more extended period. Time intervals of approximately 1 to 16 days are classified as short-term, whereas values exceeding 16 days pertain to the long-term perspective. Each heatmap provides a visual representation of the intricate interplay between Bitcoin and a distinct variable, such as gold and stock markets, as explicitly designated in the heading of each heatmap. Upward-pointing arrows (↑) and diagonal arrows (↘ and ↖) serve as indicators of Bitcoin's pivotal role as the leading influencer in the contagion dynamics between itself and the specific variable under scrutiny. This implies that the transmission of contagion is predominantly instigated by Bitcoin, affecting the other variable. In contrast, downward-pointing arrows (↓) and reverse diagonal arrows (↗ and ↙) imply that the other variable, whether it be gold or the stock markets, assumes the primary role in driving the contagion relationship between itself and Bitcoin. In such instances, the contagion predominantly originates from these variables, impacting Bitcoin. Right-pointing arrows demonstrate a positive relationship between Bitcoin and gold or stock markets, whereas left-pointing arrows indicate an inverse relationship. The black lines in the heat maps represent statistically significant relationships at a 5% level of significance. Cooler colors (blue) reflect a weaker contagion between the variables, whereas warmer colors (red) indicate a stronger contagion.