Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Looking for a safe haven against American stocks during COVID-19 pandemic

Agata Kliber
Poznan University of Economics and Business, Department of Applied Mathematics, Al.Niepodleglosci 10, Poznan, Poland

ARTICLE INFO

JEL classification:
G01
G11
G23
C58

Keywords:
Safe haven
Quantile coherency
S&P 500
COVID-19
Stablecoins
DeFi coins
Cryptocurrencies

ABSTRACT

This article aims to find the best safe-haven for stock investors in the American market since the COVID-19 pandemic outbreak. The research period covers March 2020–May 2022. Among the possible alternatives, we analyse the traditional ones: US bonds, gold, and silver, as well as the new ones: stable DeFi and CeFi coins, and most popular cryptocurrencies: Bitcoin and Ether. We study quantile coherency between S&P 500 and each asset and the respective conditional correlation. We show that the safe-haven properties of the assets varied over time and that centralized stablecoins could have been used as safe-haven against American stocks during the pandemics.

1. Introduction

The after-effect of the SARS-COV2 pandemic outbreak is the global financial crisis. Many countries experience inflation growth, which makes saving in the bank account much less remunerative than it used to be before. In such a situation, investors look for alternative means of protecting their wealth. The ones who are less risk-averse decide to invest in cryptocurrencies. Yet, the opponents claim that the risk connected with such an investment outperforms the possible earnings (Klein, Thu, & Walther, 2018; Smales, 2019). The solution could be stablecoins.

There are various definitions of stablecoins (see ECB Cryptoassets Task Force, 2020 or Bullmann, Klemm, & Pinna, 2019). Broadly speaking, these are the cryptocurrencies pegged to the asset which is considered stable, e.g. US dollar, gold, or other collaterals, against which stablecoin holdings may be exchanged. Such arrangements enable the stabilization of the value of the stablecoins.

Stablecoins can be classified by the type of the peg into (Blockchain Consultants, 2020; Kahya, Krishnamachari, & Yun, 2021): fiat stablecoins (pegged against or collateralised by fiat currencies such as the US dollar or Euro, e.g. Tether, USD Coin), crypto stablecoins (pegged against or collateralised by other virtual currencies, e.g. MakerDAO and Bitshares) and commodity stablecoins (pegged against or collateralised by a commodity, e.g. Digix Global and HelloGold). Hybrid stablecoins (e.g., Reserve, Saga) may involve more than one type of backing, such as crypto and fiat ones. There are also algorithmic stablecoins (e.g., Basis, Carbon, Terra), not backed by any asset, whose objective is to have the coin’s price as close to 1 USD as possible by algorithmically managing their supply. The last category is sovereign stablecoins, for instance, Petro, launched in Venezuela to overcome hyperinflation. Such coins are backed by and approved by a central bank or regulatory authority.

This document is the results of the research project funded by the Minister of Science and Higher Education of Poland through the Regional Initiative for Excellence programme, years 2019–2022, grant no. 004/RID/2018/19, financing 3,000,000 PLN.

E-mail address: agata.kliber@ue.poznan.pl.

https://doi.org/10.1016/j.najef.2022.101825
Received 8 March 2022; Received in revised form 29 August 2022; Accepted 26 September 2022
Available online 17 October 2022
1062-9408/© 2022 The Author(s). Published by Elsevier Inc. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).
According to Bullmann et al. (2019), an element that is common to all stablecoin initiatives is the use of software so-called “smart contracts”. The term “smart contract” is associated with so-called decentralized finance (DeFi), as opposed to centralized finance: CeFi and denotes automated contracts with pre-defined protocols hosted on blockchains (Aramonte, Huang, & Schrimpf, 2021). The difference between centralized and decentralized crypto assets depends on the type of exchange used to trade the coins. Centralized exchanges act as a third party between a buyer and a seller. On the contrary, decentralized ones allow users to execute peer-to-peer transactions without a third party.

A milestone for the evolution of the DeFi system was the development of the Ethereum network with Ether (ETH) cryptocurrency set (Aramonte et al., 2021). This technology supports smart contracts, and the term DeFi refers to the financial applications run by smart contracts on a blockchain.

Although all stablecoins use smart contracts, they can also be classified into centralized and decentralized ones (Aramonte et al., 2021; Kahya et al., 2021 or Qin, Zhou, Afonin, Lazaretti, & Gervais, 2021), depending on whether they are managed off- or on-chain. Centralized stablecoins are backed by a fiat currency in an off-chain bank account. There is an intermediary that manages the issuance via minting and redemption mechanisms. Decentralized stablecoins are usually overcollateralised by on-chain cryptocurrencies. Collateral backing is visible to everybody because funds are on a publicly verified blockchain. DeFi stablecoins record all transacting histories directly on-chain, and the centralized intermediaries get not involved. That feature makes this type of cryptocurrency more transparent. An example of a decentralized stablecoin is USD Tether, and a decentralized one — DAI.

This article studies the possibility of using CeFi and DeFi stablecoins as potential safe-havens. We define the asset as a safe-haven when it is negatively (strong safe-haven) or insignificantly (weak safe-haven) interrelated with the base one during financial turmoils. We take into account the perspective of the US investor. Therefore, we analyse the relationships in quantiles between the main US stock index, S&P 500, and traditional safe havens: US T-bonds, gold, and silver, as well as the “new” safe-havens: Bitcoin, Ether, and selected stable DeFi (DAI) and CeFi (Tether and USDC) coins. The choice of the stablecoins is based on their liquidity approximated by the market capitalization and volume of trade (based on coinmarket.com data). We claim that a safe-haven candidate should be liquid enough to enable the change of the investment position. Table 1 presents the classification of the cryptocurrencies into CeFi, DeFi and stablecoins. We note, however, that the classification into CeFi and DeFi is still “fuzzy”, and there is still a debate on what makes the coin decentralized (see Qin et al., 2021 for a detailed discussion).

We apply the quantile-coherency method proposed by Barunik and Kley (2019). The approach allows us to measure the coherency of each pair of assets in pre-specified quantiles. We analyse the relationships in quantiles from March 2020 to May 2022, dividing the period into four subperiods, depending on the pandemic intensity. We concentrate on the coherency between the extreme downfalls of S&P and other assets. Next, we investigate the coherence between the extreme downfalls of S&P and the extreme jumps of the second investment. As a robustness check, we apply the “classical” approach and investigate the correlation of the base asset with potential safe-havens, conditional on the extreme negative returns of the base asset.

We conclude that the possibility of protecting the investment was time-varying and depended on the investment horizon. During the first pandemic wave, the best safe-haven candidates were gold and Ether (the assets exhibited negative or insignificant coherency between the extreme declines and positive – for some frequencies – between the 0.05|0.95 quantiles). The set of potential safe-havens gradually widened and, from September 2020, started to encompass stablecoins. After a year, all traditional safe-havens could have been used as investment protection.

From the second test we learned that stablecoins could have been successfully used as hedges or safe-havens in each sub-period. The instruments exhibited a negative (USDC) or extremely low correlation with the base asset (comparable to the correlation of gold) and the correlation diminished as a reaction to the extreme declines of S&P - at least in some periods.

The main difference between the two applied methods lies in the strength of the growth of the second asset during the S&P downfalls. In the first procedure, we make sure that the prices do not excessively decline together (1) and check whether the possible safe-haven experiences extreme increases during the excessive S&P declines (2). In the second method, we verify whether the possible safe-haven does not significantly change its value during the stocks’ downfalls or whether it grows in some (not necessarily extreme) amount.

Thus, the possibility of the usage of stablecoins as safe-havens varies. The quantile coherency analysis revealed that USDT and USDC could have been interchangeably used to protect the investment in the American stocks due to the negative or insignificant correlation between extreme declines and the positive (or insignificant) between the asymmetric quantiles. The test based on conditional correlation confirms the result.

The rest of the paper is structured as follows. First, we briefly summarize the most up-to-days articles dealing with the problem of finding safe-haven assets, particularly among cryptocurrencies. Next, we describe the data characteristics and explain the methodology. Eventually, we present the obtained results and discuss them.

1 Up to May 2022 one of the most popular decentralized stablecoin was Terra–LUNA. Terra was an open-source blockchain payment platform for algorithmic stablecoins. It consisted of two main cryptocurrency tokens: Terra and Luna. The stablecoin was an algorithmic one — LUNA could be burnt in order to “mint” Terra to stabilize it whenever it was loosing its 1:1 peg to the dollar. LUNA had its value pegged to the dollar on a one-is-to-one basis, too. LUNA’s stability was ensured by backing it with cryptocurrencies, especially Bitcoin. In May, 2022, the Terra-LUNA arbitrage scheme collapsed, causing the “May mayhem” and questioning the safeness of the stablecoins (Chandrasekhar, 2022).
2. Literature review

There are many papers devoted to the analysis of safe-haven properties of various assets. Historically, first papers concentrated on gold (see: Baur & Lucey, 2010 or Baur & McDermott, 2010) and other precious metals (e.g. Lucey & Li, 2015 or Pierdziŏch, Risse, & Rohloff, 2016). Scholars verified also the analogous properties of oil (see for instance: Elie, Naji, Dutta, & Uddin, 2019, Musiałkowska, Kliber, Świerczyńska, & Marszałek, 2020, Liu, Naeem, Rehman, Farid, & Shahzad, 2020) or other commodities (Kaczmarek, Będowska-Sójka, Grobelny, & Perez, 2022).

With the growing popularity of cryptocurrencies, the researchers focused their attention on Bitcoin. Conclusions on the safe-haven properties of the latter are mixed. Some authors strongly deny the existence of such ones (Klein et al., 2018; Smales, 2019), while others demonstrate that they are time-varying (Będowska-Sójka & Kliber, 2021; Shahzad, Bouri, Roubaud, Kristoufek, & Lucey, 2019), depending on other factors, such as e.g. the economic situation of the country (Kliber, Marszałek, Musiałkowska, & Świerczyńska, 2019; Musiałkowska et al., 2020), economic uncertainty (Hsu, Sheu, & Yoon, 2021) or current volatility regime (Ahmed & Sarkodie, 2021). Fewer papers concentrate on the safe-haven properties of other popular cryptocurrencies, most often on Ether. For instance, Mescheryakov and Ivanov (2020) demonstrated that Ether was a hedge against both the U.S. stock market and the gold market during the pre-COVID period. Będowska-Sójka and Kliber (2021) compared the safe-haven properties of Ether and Bitcoin during various market turbulences. Feng, Wang, and Zhang (2018) evaluated the characteristics of seven cryptocurrencies, including Bitcoin and Ether, and proved that both of them acted as diversifiers against the stock market but not as safe-havens. The results were further supported by Conlon, Corbet, and McGee (2020), who concluded that over April 2019–April 2020, Bitcoin and Ether did not perform as safe havens against international stocks — as opposed to Tether. Yet, Huyhn, Nasir, Vo, and Nguyen (2020) highlight the high volatility of the latter and suggest that a portfolio constructed from smaller cryptocurrencies should be rebalanced by including gold in it. Eventually, Mensi, Rehman, Al-Yahyae, Al-Jarah, and Kang (2019), who studied the commonalities between Bitcoin and five major cryptocurrencies (Dash, Ethereum, Litecoin, Monero, and Ripple), concluded that investors obtain the best portfolio risk reduction through mixing Bitcoin with other coins.

When it comes to the current crisis, lots of recent studies show that Bitcoin lost its safe-haven property during the pandemic (Chemkha, BenSaïda, Ghorbel, & Tayachi, 2021; Conlon et al., 2020; Conlon & McGee, 2020; Raheem, 2021; Rubbaniy, Khalid, & Samitas, 2021). Additionally, investors became more risk-averse (Huber, Huber, & Kirchler, 2021). For these reasons, stablecoins may appear an interesting alternative to protect wealth. That is why we find it important to analyse such properties of the most popular stablecoins.

Up to date, few researchers focused their attention on the safe-haven properties of stablecoins. One of the exceptions is the technical report of Baumöhl and Vyrost (2020), which analysed whether stablecoins can be treated as safe havens against the non-stable cryptocurrencies. The authors studied intraday data for selected cryptocurrencies and stablecoins for the whole of 2019. A similar analysis is presented by Wang, Ma, and Wu (2020), who conclude, inter alia, that gold-pegged stablecoins perform worse as safe havens than USD-pegged ones and that the safe-haven property of stablecoins changes across market conditions. Vukovic, Maiti, Grubisic, Grigorieva, and Frömml (2021) demonstrated that Tether could have been used as a safe-haven against the American stocks during the first wave of the pandemic. Xie, Kang, and Zhao (2021) confirmed the ability of Tether to act as a safe-haven against traditional cryptocurrencies before and during the pandemic. Similar conclusions can be found in Baur and Hoang (2021) and Goodell and Goute (2021).

This article extends that strand of literature and focuses on the possibility of using stablecoins as safe-havens against American stocks and compares this possible ability with the effectiveness of the traditional safe-havens and the “main” cryptocurrencies: Bitcoin and Ether. Contrary to other authors, we also differentiate between the De-Fi and Ce-Fi cryptocurrencies. We study the relationships between the assets during different COVID phases to verify the stability of these properties.

Modelling approaches. There are many methods to verify whether an asset is a safe-haven or not. One of the most commonly applied is the approach used, for instance, by Baur and Lucey (2010) or (Bouri, Molnár, Azzi, David, & Ivar, 2017). The authors estimate the conditional correlation between the base assets and the possible safe-haven using the dynamic conditional correlation model (further: DCC). Next, using a linear regression model, they verify whether the correlation declined significantly below 0 during the most extreme drops in base-asset price. A similar approach can be found in Kliber et al. (2019), but the authors estimate DCC-MSV instead of DCC-MGARCH. Also, Będowska-Sójka and Kliber (2021) use DCC-MSV model but analyse the 95% credibility interval of the dynamic correlation during the extreme downturns.

Yet another solution is to use threshold regression (Hossfeld & MacDonald, 2015; Kliber & Świerczyńska, 2019) or regime-switching approach (Ahmed & Sarkodie, 2021) and verify the coefficients in the high-stress regimes. Some other authors use copula models and analyse dependencies in tails, see e.g. Bouri, Gupta, Lau, Roubaud, and Wang (2018), Kumamoto and Zhuo (2021) and Nguyen, Bedoui, Majdoub, Guesmi, and Chevallier (2020). Eventually, the methods that analyse the data in the time and frequency domain are gaining more and more popularity. Such technique was applied, for instance, by Jiang, Lie, Wang, and Mu (2021), who analysed the diversifier properties of cryptocurrencies against stocks, or by Let and Siemaszkiewicz (2020), who investigated safe-haven properties of Bitcoin, gold, and fine wine market against stocks.

The main difference between the “classical” approach, devoted to correlation modelling, and the approaches based on the analyses of tails of the joint distribution is the part of the distribution on which the researcher concentrates. In the correlation analysis, one estimates the conditional correlation between the standardized returns. Thus, the main focus is on the centre of the distribution, meaning that one is interested in how the returns deviate from their expected (average) value. Next, one estimates the regression model and investigates how the correlation behaves when the base asset experiences extreme drops. The positive
business is conducted based on that price twice a day by five LBMA Market Makers who comprise the London Gold Market Fixing Limited (LGMFL). The price is then announced as the ‘Fixed’ price for gold. All

extreme coefficient implies that the correlation grew during the moments of the declines in the base asset. Such a result does not indicate that the second asset also experienced such extreme declines but that, usually, together with the severe drops in the base asset, declines of some magnitude in the second instrument appeared as well. We also note that, in this approach, we can detect only linear relationships between the assets.

On the other hand, in the approaches that focus on quantiles (quantile regressions, quantile coherency, etc.), we do not study the “average” behaviour of the assets. Instead, we concentrate on the co-occurrence of rare events. Positive coherency between the lowest quantiles denotes a high probability that the extreme downfalls of both assets would happen simultaneously. That may suggest the existence of a common external factor that affects both instruments in the same way. Positive coherency between the lowest quantile of the base asset and the highest quantile of the second one denotes a high probability of the co-occurrence of severe declines in the first one and extreme growths in the second one. Such events are rather rare in financial markets but allow for perfect protection of the investment during market turbulences.

In our paper, we apply the quantile coherency approach and estimate the quantile coherency between the residuals from univariate GARCH models between S&P and potential safe-havens. We add to the existing literature by extending the analysis to the frequency domain. Following the remark in Baur and Dimpfl (2021), that the “standard” safe-haven test (i.e. the one based on the analysis of the reaction of conditional correlation on extreme drops in base asset) is more general than asymmetric connectedness, we supplement the results by the correlation analysis.

3. The data

We analyse log-returns\(^2\) of S&P 500 and potential safe-haven assets from April 2020 to May 2022. We consider the following types of safe-havens:

- traditional ones: gold, silver and 10-years US bonds;
- two most popular cryptocurrencies: Bitcoin and Ether;
- DeFi stablecoin: Dai;
- CeFi stablecoins: Tether and USDC.

**Tether (USDT)** is a blockchain-based CeFi stablecoin whose tokens are backed by an equivalent amount of U.S. dollars. In October 2021, USDT was the fifth-largest cryptocurrency by market capitalization, worth more than 68 billion USD (Reeves, 2021). USD Coin, **USDC**, is a stablecoin issued by CENTRE — a joint venture between Coinbase and Circle. The cryptocurrency is backed by U.S. dollar-denominated assets held at regulated and audited U.S. financial institutions. It is the second stablecoin (after Tether) by market capitalization (data for February 2022).

**Dai (DAI)**, founded in 2014, was the first decentralized, collateral-backed cryptocurrency. It attempts to maintain a stable 1:1 value with the U.S. dollar by locking other crypto assets in contracts. More precisely, DAI maintains its value by using collateralized debt denominated in Ether (ETH), Ethereum’s cryptocurrency (Kraken, 2021).

In Table 1 we present the classification of the cryptocurrencies used in the study into CeFi, DeFi and stablecoins.

We obtained the data on gold and silver through data.nasdaq.com database. These are US-dollar closing prices from LBMA Market.\(^3\) We obtained the data of S&P 500 and 10-years US from CEIC (ISI Emerging Markets Group Company) database. Prices of all cryptocurrencies come from the platform coinmarketcap.com. The price of any cryptoasset is a volume weighted average of market pair prices for the cryptoasset.\(^4\)

Since the cryptocurrency exchanges work seven days a week, while during weekends and holidays the classical assets are not traded, in the first step of the research, we needed to merge the series into one database of equal series length. The data covered the period from 01.04.2020 to 01.05.2022. Within this timespan, the series of cryptocurrencies were the longest and consisted of 761 observations (see Table 9), while gold data were the shortest. To merge the series, we deleted the “excessive” observations. In summary, in the case of SPX and silver, we deleted 18 items, in the case of bonds — 15, gold — 14, and cryptocurrencies — 254.

---

2 The log-return were calculated as: \( r_t = \ln \left( \frac{P_t}{P_{t-1}} \right) \), where \( r_t \) denotes the log-return observed at day \( t \), while \( P_t \) - the price of the instrument at day \( t \).

3 The London Gold Fixing Companies set the prices for gold that are globally considered the international standard for pricing of gold. The Gold price in London is set twice a day by five LBMA Market Makers who comprise the London Gold Market Fixing Limited (LGMFL). The price is then announced as the ‘Fixed’ price for gold. All business is conducted based on that price. (https://data.nasdaq.com/data/LBMA/GOLD-gold-price-london-fixing).

4 https://support.coinmarketcap.com/hc/en-us/articles/36004395752-Price-Market-Pair-Cryptoasset-, accessed: 26.08.2022.
A. Kliber

Fig. 1. Returns of S&P 500 (a), US 10-years bonds (b), gold (c), silver (d), DAI (e), Tether (f), USDC (g), ether (h) and Bitcoin (i) from April 2020 to May 2022. Note Returns of traditional safe-havens are painted green, stablecoins — blue, while cryptocurrencies — red.

We are aware that deleting the “excessive” information may result in the growth of the series’ volatility. On the other hand, no method of data imputation is perfect (see e.g. Saad, Chaudhary, Karray, & Gaudet, 2020) and always results in introducing some artificial information into the dataset. In Table 9 (Appendix) we present the detailed information on data preparation.

In Fig. 1, we present the returns of S&P 500 and potential safe havens: US bonds, gold, silver, DeFi (DAI), and CeFi stablecoins (Tether and USDC). The figure is supplemented by Table 2, where we present the basic descriptive statistics of the assets. Through the paper, we apply the following scheme to each chart. The charts corresponding to the “classical” safe-havens are painted in green, stablecoins — in blue, and other cryptocurrencies — in red. The graphs of the base asset (S&P) are displayed in black.

Standard deviations of CeFi stablecoins were the smallest among all analysed assets, including gold. Unexpectedly, the US bonds seemed to be more volatile than the US stocks (measured by standard deviation). This phenomenon can be explained by the COVID impact on sovereign bonds and sovereign risk. For instance, (Paule-Vianez, Orden-Cruz, & Escamilla-Solano, 2021) analyse the influence of fear generated by the coronavirus on various bond markets and show its significant impact on the yields, including the US bonds. The authors demonstrate that a one-point increase in COVID-induced fear was associated with an increase in the weekly change in the sovereign bond yield of around 0.0007% (see also Andries, Ongen, & Sprincean, 2021 for the analysis of the reaction of the whole yield curve). When it comes to the stock market, initially, its reaction was even stronger (Liu, Kong, Xiao, Zhang, Zhou, & Qi, 2022) (results for the period October 2019–April 2020). Yet, as (Gao, Ren, & Umar, 2021) note, “the strong growth of daily new cases, which continued for months, has made the US stock market insensitive to COVID-19”. Besides, the loose interest rate policy has effectively suppressed the volatility of the American stock market.

It is interesting to compare excess kurtosis of the assets. The stablecoins of relatively low volatility have the highest kurtosis of 30 (Tether), 18 (DAI) and 16 (USDC). Such results stem from the fact that the cryptocurrencies keep their almost-constant value, but from time to time, they are prone to large shocks (see Fig. 1: (e)–(g)). Stablecoins (apart from USDC) were right-skewed, the same as silver. The rest of the traditional safe-havens (bonds and gold) were left-skewed.
4.1. GARCH models

Let us denote by \( y_t \) a vector of time series, and by \( \Omega_{t-1} \) - the set of information available up to the moment \( t-1 \). Let us denote the conditional mean of \( y_t \) as:

\[
y_t = E \left( y_t | \Omega_{t-1} \right) + \epsilon_t, \tag{1}
\]

where \( E(\cdot | \cdot) \) is the conditional expectation operator, and \( \epsilon_t \) - the disturbance term with \( E \left( \epsilon_t \right) = 0, E \left( \epsilon_t, \epsilon_s \right) = 0, \forall t \neq s \). In the case of daily financial time-series, conditional mean is typically modelled with one of AR, MA or ARMA models, while the \( \epsilon_t \) can be decomposed in the following way:

\[
\epsilon_t = z_t \sigma_t, \tag{2}
\]

where \( z_t \sim iid \) with mean 0 and unit variance. If \( \sigma_t \) can be expressed as:

\[
\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{3}
\]

Note: s.d. denotes standard deviation, excess kurtosis is the kurtosis of the asset minus 3 (kurtosis of normal distribution). For clarity, returns were multiplied by 100.

For comparison, in the Appendix, we present the descriptive statistics of the same data when the missing observations were interpolated. We note that the standard deviations are lower, as expected, but the main conclusions do not change. The highest standard deviation was obtained for Terra, Ether, and Bitcoin. The value of kurtosis in Table 10 is higher for S&P, bonds, gold, silver, as well as Bitcoin and Ether than in Table 2.

4. The model

Generally, the literature defines safe-havens as assets that are negatively interrelated with the base ones during market distress. The interrelations can be measured, for instance, with a correlation coefficient. Some scholars differentiate between proper and weak safe-havens. The weak one may be uncorrelated with the base instrument during the market turmoils. Yet, such relationships should hold during hectic times. If they are present during normal market conditions, such an asset is named proper or weak hedge, respectively. The instrument that is, on average, positively correlated with the base one is called a diversifier (see e.g. Kliber et al. (2019) for discussion).

There is no consensus in the literature, whether a safe-haven asset should be a safe one. For instance (Baur & Dimpfl, 2021) differentiate between the safe-haven and safe instruments.

We measure the safe-haven properties of assets using quantile coherency. We analyse the coherency between the most extreme downfalls of S&P as well as between the most extreme upper jumps of the remaining assets (i.e. below 0.05 and above the 0.95 quantiles). A positive relationship between the 0.05 and 0.05 quantile means that the extreme downfalls of the two instruments moved together (Baumöhl, 2019). A negative coherency between the 0.95 and 0.05 quantile would indicate that the above-average increases of one asset and similar decreases of the other one occurred simultaneously. A negative coherency between the 0.95 and 0.05 quantile would mean that these two assets moved together (Baumöhl, 2019).

Taking all the above into account, we would conclude that the asset can perform a role of a safe-haven when the coherency between the extreme low quantiles is positive (strong safe-haven) or insignificant (weak safe-haven). The weak one may be uncorrelated with the base instrument during the market turmoils. Yet, such relationships should hold during hectic times. If they are present during normal market conditions, such an asset is named proper or weak hedge, respectively. The instrument that is, on average, positively correlated with the base one is called a diversifier (see e.g. Kliber et al. (2019) for discussion).

In the first step of the research, we estimate a series of GARCH models. Next, we collect the residuals and standardize them using the estimated conditional variance. Using the residuals, we estimate quantile coherency graphs for the asymmetric quantiles is positive (strong safe-haven) or insignificant (weak safe-haven).

Table 2

| Category           | Asset | Mean | Sd  | Min  | Max  | Kurtosis | Skewness |
|--------------------|-------|------|-----|------|------|----------|----------|
| Base asset         | SPX   | 0.101| 1.171| –6.075| 6.797| 6.552    | –0.268   |
| Traditional safe havens | US bonds | 0.304| 3.990| –18.760| 14.732| 5.356    | –0.052   |
|                    | gold  | 0.038| 1.042| –5.265| 3.580| 5.455    | –0.543   |
|                    | silver| 0.101| 2.060| –9.139| 10.209| 6.896    | 0.238    |
| DEFI stablecoins   | DAI   | –0.004| 0.588| –3.039| 4.610| 18.840   | 0.998    |
| CEFI stablecoins   | USDC  | 0.001| 0.160| –0.712| 1.239| 16.102   | 0.891    |
|                    | USDT  | –0.001| 0.226| –1.899| 1.692| 30.749   | –0.844   |
| Cryptocurrencies   | BTC   | 0.348| 4.444| –14.811| 19.153| 4.838    | –0.062   |
|                    | ETH   | 0.598| 6.010| –31.746| 32.497| 6.890    | –0.062   |

Note: s.d. denotes standard deviation, excess kurtosis is the kurtosis of the asset minus 3 (kurtosis of normal distribution). For clarity, returns were multiplied by 100.
we say that it follows a GARCH(\(p, q\)) process (see: Bollerslev, 1986 for details).

In the paper, we also estimate also another two kinds of models that account for so called asymmetrical reaction of volatility to good and bad news: APARCH and GJR-GARCH.

The APARCH model (Ding, Granger, & Engle, 1993) is parametrized in the following way:

\[
\sigma_t^2 = \omega + \sum_{i=1}^{q} \gamma_i (|\epsilon_{t-i}| - \gamma_i \epsilon_{t-i})^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2,
\]

where \(\gamma\) is an asymmetry parameter. The model is more flexible, since depending on the estimated value of \(\delta\) we can model different types of non-linear dependencies, other than the conditional variance.

A GJR model (Glosten, Jagannathan, & Runkle, 1993) takes the following form:

\[
\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i \epsilon_{t-i}^2 + \gamma_i \epsilon_{t-i} \epsilon_{t-i} I(\epsilon_{t-i} < 0)) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2,
\]

where \(I(\cdot)\) is an indicator function (i.e. \(I(\epsilon_{t-1} < 0) = 1\) if \(\epsilon_{t-1} < 0\) and 0 otherwise), and \(\gamma\) denotes the asymmetry parameter. All the models have been estimated using R package rugarch of Ghahanos (2020).

4.2. Quantile coherency

In the second step of the research, we collect the standardized residuals from the GARCH models and apply the quantile coherency measure proposed by Barunik and Kley (2019). The method allows for understanding the behaviour of joint quantiles of the returns. In our research we are especially interested in the dependencies in tails. The measure defined by Barunik and Kley (2019), instead of the conditional variance, other than the conditional variance.

To measure the dependence structure of \((X_t)_{t \in \mathbb{Z}}\), we use the matrix of quantile cross-covariance kernels \(\Gamma_k(\tau_1, \tau_2) = \gamma_k^{j_1,j_2}(\tau_1, \tau_2)_{j_1,j_2=1,\ldots,d}\), where (Barunik & Kley, 2019):

\[
\gamma_k^{j_1,j_2}(\tau_1, \tau_2) = \text{Cov}(I(X_{t+k,j_1} \leq q_{j_1}(\tau_1)), I(X_{t+k,j_2} \leq q_{j_2}(\tau_2))
\]

(6)

The symbol \(\text{Cov}(\cdot)\) denotes the indicator function that takes value 1 for \(x \in A\) and 0 otherwise.

Barunik and Kley (2019) extend the method to the frequency domain and define the matrix of quantile cross-spectral density kernels \(\mathbb{g}^{j_1,j_2}(\omega; \tau_1, \tau_2) := (\hat{f}^{j_1,j_2}(\omega; \tau_1, \tau_2))_{j_1,j_2=1,\ldots,d}\), where (Barunik & Kley, 2019):

\[
\hat{f}^{j_1,j_2}(\omega; \tau_1, \tau_2) := (2\pi)^{-1} \sum_{k=-\infty}^{\infty} \gamma_k^{j_1,j_2}(\tau_1, \tau_2) e^{-i\omega k}.
\]

(7)

Subsequently, the authors propose a quantile coherency kernel — the quantity that measures the dynamic dependence of the two processes:

\[
\mathbb{g}^{j_1,j_2}(\omega; \tau_1, \tau_2) := \hat{f}^{j_1,j_2}(\omega; \tau_1, \tau_2) \bigg/ \left( (\hat{f}^{j_1,j_1}(\omega; \tau_1, \tau_1) \hat{f}^{j_2,j_2}(\omega; \tau_2, \tau_2))^{1/2} \right).
\]

(8)

The authors define the estimator for the quantile cross-spectral density, called later the rank-based copula cross-periodograms (shortly: the CCR-periodograms), as:

\[
I_{n,R}^{j_1,j_2}(\omega; \tau_1, \tau_2) := \frac{1}{2\pi n} d_n^{j_1,j_2}(\omega; \tau_1) d_n^{j_2,j_2}(\omega; \tau_2),
\]

(9)

where (Barunik & Kley, 2019):

\[
d_n^{j,j}(\omega; \tau) := \frac{1}{n-1} \sum_{i=0}^{n-1} \left\{ \hat{F}_{n,j}(X_{t,i}) \leq \tau \right\} e^{-i\omega \tau} = \frac{1}{n} \sum_{i=0}^{n-1} \{ R_{n,i,j} \leq n \tau \} e^{-i\omega \tau}.
\]

(10)

\(\hat{F}_{n,j}(x) := n^{-1} \sum_{i=0}^{n-1} I(X_{t,i} \leq x)\) denotes empirical distribution function of \(X_{t,i}\), while \(R_{n,i,j}\) - the maximum rank of \(X_{t,i}\) among \(X_{0,j}, \ldots, X_{n-1,j}\).

Let us denote the matrix of CCR-periodograms by Barunik and Kley (2019):

\[
I_{n,R}^{j_1,j_2}(\omega; \tau_1, \tau_2) := \left( I_{n,R}^{j_1,j_2}(\omega; \tau_1, \tau_2) \right)_{j_1,j_2=1,\ldots,d}
\]

(11)
Table 3
Estimates of ARMA(0,0)-GARCH(1,1) with student distribution for S&P 500.

| Parameter | Estimate | Std error | t stat | p.value |
|-----------|----------|-----------|--------|---------|
| μ         | 0.137    | 0.038     | 3.621  | <0.000  |
| α         | 0.166    | 0.239     | 0.695  | 0.487   |
| β         | 0.797    | 0.307     | 2.593  | 0.010   |
| ν         | 6.928    | 0.899     | 7.708  | <0.000  |
| α         | 0.051    | -         | -      | -       |

Note: By v we denote the estimated number of the degrees of freedom. The model was estimated using variance-targeting option, i.e. α is equal to the unconditional variance of the process. The model explained linear and non-linear dependencies in data (according to Ljung–Box test for standardized residuals and ARCH test), passed Pearson’s goodness of fit test for distribution and sign-bias test for asymmetric effects in volatility. All parameters are stable according to Nyblom stability test.

Kley, Volgushev, Dette, and Halin (2016) show that the CCR periodograms fail to estimate \( \hat{f}_{1/2}^{1/2} (\omega; \tau_1, \tau_2) \) consistently. Therefore, Barunik and Kley (2019) propose to smooth \( I_{n,R}^{1/2} (\omega; \tau_1, \tau_2) \) across frequencies. For this purpose, they consider:

\[
\hat{G}_{n,R}^{1/2} (\omega; \tau_1, \tau_2) := \frac{2\pi}{n} \sum_{s=1}^{n-1} W_s (\omega - 2\pi s/n) I_{n,R}^{1/2} (2\pi s/n, \tau_1, \tau_2)
\]

where \( W_s \) denotes a sequence of weight functions. The estimator of quantile coherency is given as (Barunik & Kley, 2019):

\[
\hat{\gamma}_{n,R} (\omega; \tau_1, \tau_2) := \left( \frac{\hat{G}_{n,R}^{1/2} (\omega; \tau_1, \tau_2)}{\hat{\gamma}_{n,R}^{1/2} (\omega; \tau_1, \tau_2)} \right)_{j_1,j_2=1,\ldots,d}
\]

where:

\[
\hat{G}_{n,R}^{1/2} (\omega; \tau_1, \tau_2) := \frac{\hat{G}_{n,R}^{1/2} (\omega; \tau_1, \tau_2)}{\hat{\gamma}_{n,R}^{1/2} (\omega; \tau_1, \tau_2)} \hat{\gamma}_{n,R}^{1/2} (\omega; \tau_2, \tau_2)^{1/2}
\]

5. Results

5.1. Volatility analysis

In Tables 3–6 we present the estimates of GARCH models for each of the asset. The table is accompanied by Fig. 2. We note that the y-axis has a different scale for each figure. Thus, the less volatile traditional safe-haven was gold, followed by silver. The volatility of the US-T-bonds exceeded the volatility of the base asset (S&P 500) and remained high even when the volatility of the index diminished. When we compare the volatilities of the “new” safe-havens, we observe very different patterns. Volatilities of USDC and Tether were visibly lower than the volatility of DAI but their relative growths were much higher and steeper.

We chose an appropriate volatility model for each asset based on its ability to:

• explain all linear and non-linear dependencies in the data;
• explain the possible asymmetry in volatility (based on the sign-bias test results);
• model the distribution of returns properly (based on Pearson’s goodness-of-fit test).

We always started with the simple ARMA(1,0)-GARCH(1,1) model (see Hansen and Lunde (2005) for the study on the superiority of the simple GARCH(1,1) over its more complex counterparts) with Student distribution. We complicated the model if it did not pass the diagnostic tests outlined above. Only in the case of silver, we did not succeed to explain the positive asymmetry in volatility. Among the best models: ARMA(1,0)-GJR-GARCH(1,3) with skewed generalized error distribution, ARMA(3,0)-EGARCH(1,1), ARMA(3,0)-APARCH(1,1) with skewed Student distribution and ARMA(3,0)-GJR-GARCH(1,1) with skewed Student distribution we chose the latter one, based on the Bayesian information criterion.

We note that the univariate GARCH models were well-fitted: in each case, all the linear and non-linear dependencies are explained (as confirmed by the Ljung–Box test for the standardized residuals and ARCH test), Pearson’s goodness of fit test, sign-bias test for possible asymmetry in conditional variance (apart from silver). Some parameters did not pass the Nyblom stability test which means, that the nature of the model may have changed over time.

In the case of S&P, the best model was ARMA(0,0)-GARCH(1,1) with Student distribution. For the precious metals, the best models were the asymmetrical ones: APARCH (gold) and GJR-GARCH (silver). The parameter of asymmetry was in all the cases negative, which signifies the higher impact of negative returns on volatility than the positive ones. In the case of gold, we estimated the APARCH models, which means that we modelled not the conditional variance, but conditional standard deviation to the power of 3.5. The best model for bonds was again ARMA(1,0)-GARCH(1,1) one, and the asymmetry was modelled through the distribution (Student’s skewed one).
Table 4  
Volatility models with skewed student distribution — traditional safe-havens.

| Parameter | Estimate | std.error | t.stat | p.value |
|-----------|----------|-----------|--------|---------|
| US T-BONDS: ARMA(1,0)-GARCH(1,1) | | | | |
| $\mu$ | 0.304 | 0.147 | 2.074 | 0.038 |
| $\alpha$ | 0.080 | 0.025 | 3.133 | 0.002 |
| $\beta$ | 0.889 | 0.039 | 22.509 | <0.001 |
| $\gamma$ | 1.042 | 0.068 | 15.217 | <0.001 |
| $\omega$ | 7.535 | 2.151 | 3.503 | <0.001 |
| $\nu$ | 0.502 | NA | NA | NA |

GOLD: ARMA(0,0)-APARCH(1,1)

| Parameter | Estimate | std.error | t.stat | p.value |
|-----------|----------|-----------|--------|---------|
| $\mu$ | 0.085 | 0.040 | 2.131 | 0.033 |
| $\alpha$ | 0.005 | 0.000 | 23.380 | <0.001 |
| $\beta$ | 0.890 | 0.001 | 793.621 | <0.001 |
| $\gamma$ | -0.900 | 0.200 | -4.498 | <0.001 |
| $\delta$ | 3.500 | 0.011 | 323.942 | <0.001 |
| $\nu$ | 5.334 | 1.427 | 3.738 | <0.001 |
| $\omega$ | 0.073 | NA | NA | NA |

SILVER: ARMA(3,0)-GJR-GARCH(1,1)

| Parameter | Estimate | std.error | t.stat | p.value |
|-----------|----------|-----------|--------|---------|
| $\mu$ | 0.088 | 0.060 | 1.470 | 0.142 |
| $\alpha$ | -0.025 | 0.045 | -0.564 | 0.573 |
| $\beta$ | 0.002 | 0.040 | 0.049 | 0.961 |
| $\gamma$ | -0.068 | 0.039 | -1.746 | 0.081 |
| $\delta$ | 0.050 | 0.008 | 6.133 | 0.000 |
| $\nu$ | 0.969 | 0.000 | 6462.166 | <0.001 |
| $\omega$ | -0.067 | 0.016 | -4.110 | 0.000 |
| $\xi$ | 1.015 | 0.060 | 16.792 | 0.000 |
| $\nu$ | 3.990 | 0.535 | 7.457 | 0.000 |
| $\omega$ | 0.060 | NA | NA | NA |

Note: By $\nu$ we denote the estimated number of the degrees of freedom, and by $\kappa$ - the skewness value in Student distribution. The model was estimated using variance-targeting option, i.e. $\omega$ is equal to the unconditional variance of the process. All the models explained linear and non-linear dependencies in data (according to Ljung-Box test for standardized residuals and ARCH test), passed Pearson's goodness of fit test for distribution and sign-bias test for asymmetric effects in volatility (apart from silver, where the positive asymmetry remained). All parameters are stable according to Nyblom stability test. Note also that the stability condition in GJR-GARCH model: $\alpha + \beta + 0.5 \cdot \gamma < 1$ is met and amounts to 0.986.

Eventually, for all the cryptocurrencies, the best model was again GARCH(1,1). We note that the number of degrees of freedom in the Student distribution for Ce-Fi stablecoins was smaller than four, which signifies the lack of kurtosis, and can be the result of extreme returns in the processes.

5.2. Analysis of quantile coherency

The conditional standard deviations obtained from GARCH models were used to standardize the residuals and estimate the quantile coherency measures. In Figs. 3–8, we present the 95% confidence intervals of the coherencies between the most extreme downfalls (below 0.05 quantile) of S&P and potential safe-havens (Figs. 3–5), as well as between most extreme downfalls of S&P and most extreme increases (above 0.95 quantile) of safe-haven candidates (Figs. 6–8). If the whole 95% interval covers zero, we conclude that the relationship is not statistically significant. We note that we do not interpret the exact values of the coherency but concentrate on whether it is statistically different from zero (i.e. the interval does not cover zero values). If the condition is met, we analyse whether the interval covers positive or negative values.

One of the stylized facts about the stock markets is that extreme negative returns contribute to a higher increase in volatility of the asset than positive ones of the same magnitude. Such a phenomenon is called “leverage” or “negative asymmetry” and was first described by Black (1976). One possible explanation of the phenomenon comes from behavioural finance theories and states that large drops can cause panic and irrational investors’ behaviour. Such hysteria can spread to large parts of the market, leading to extreme declines in other assets (Baruník & Kley, 2019), regardless of their economic fundamentals. Thus, in the event of excessive downfalls, the interconnection between the markets can grow (see e.g. the classical paper of Forbes and Rigobon (2002) for the discussion about financial contagion). Therefore, we could expect a higher probability of joint declines in the returns of both instruments than the probability of asymmetric relationships.
Table 5

Estimates of volatility models for Bitcoin and Ether.

| Parameter          | Estimate | std.error | t.stat | p.value |
|--------------------|----------|-----------|--------|---------|
| BTC: ARMA(0,0)-GARCH(1,1)  |          |           |        |         |
| $\mu$              | 0.290    | 0.178     | 1.631  | 0.103   |
| $\alpha$           | 0.053    | 0.009     | 6.118  | <0.001  |
| $\beta$            | 0.936    | 0.014     | 67.691 | <0.001  |
| $\kappa$           | 1.005    | 0.058     | 17.190 | <0.001  |
| $\nu$              | 4.596    | 0.640     | 7.178  | <0.001  |
| $\omega$           | 0.204    |           |        |         |
| ETH: ARMA(0,0)-GARCH(1,1)  |          |           |        |         |
| $\mu$              | 0.547    | 0.242     | 2.256  | 0.024   |
| $\alpha$           | 0.061    | 0.025     | 2.433  | 0.015   |
| $\beta$            | 0.896    | 0.046     | 19.386 | <0.001  |
| $\kappa$           | 0.986    | 0.064     | 15.387 | <0.001  |
| $\nu$              | 4.815    | 0.762     | 6.321  | <0.001  |
| $\omega$           | 1.551    |           |        |         |

Note: By $\nu$ we denote the estimated number of the degrees of freedom, and by $\kappa$ - the skewness value in Student distribution. The model was estimated using variance-targeting option, i.e. $\omega$ is equal to the unconditional variance of the process. All the models explained linear and non-linear dependencies in data (according to Ljung–Box test for standardized residuals and ARCH test), passed Pearson’s goodness of fit test for distribution and sign-bias test for asymmetric effects in volatility. All the parameters passed Nyblom stability test apart from: $\mu$ and $\nu$ for BTC and $\nu$ for ETH.

For this reason, we first inspect the coherence between the large drops (below 0.05 quantile). The positive relationship between the 0.05 and 0.05 quantile means that the abnormal downfalls of the two instruments occurred together. The negative one denotes that extremely low returns are negatively associated. The latter means that it is advisable to diversify a portfolio using such an asset.

As the main point of interest in our study is whether we can find a safe haven instrument against the American stocks, we are also interested in the asymmetrical relationship between the instruments. In other words, we look for the positive and statistically significant relationship between the extreme drops in S&P returns and increases in the second asset in the portfolio. Therefore, we also analyse relationships between the 0.05|0.95 quantiles.

Positive coherency between the 0.95 safe-haven and 0.05 S&P quantile signifies that the extreme increases of one instrument and the abnormal decreases of the second one occurred at the same time. When we observe negative coherency between the 0.95 and 0.05 quantile, this means that these two assets moved together.

Taking all the above into account, we would conclude that the asset can perform a role of a safe-haven, when the coherency between the extreme low quantiles is insignificant (weak safe-haven) or negative (strong safe-haven), while the coherency between the asymmetric quantiles is positive (strong safe-haven) or insignificant (weak safe-haven).

We also note that the relationships can change depending on the analysed horizon. Baruník and Kley (2019) show that long-term fluctuations in quantiles of the joint distribution may differ from the ones in the short term because market participants of different investment horizons may value the investment risk differently. On x-axes in Figs. 3–8 we present the frequencies (in daily cycles). Since the data are daily, the highest possible frequency, 0.5, indicates 0.5 cycles per day, which translates into two days. Precise frequencies do not have an economic interpretation (Baruník & Kley, 2019) but can be re-calculated into the investment terms. For instance, frequency 0.2 denotes 0.2 cycles per day and can be interpreted as a 5-days horizon or one (working) week. In this way, one can study how the cycles of different lengths are connected across quantiles of the joint distribution. Particularly, in each Figure, we denote by red vertical line the investment horizons corresponding to two days (2D), one week (1 W), and one month (1M).

As already noted, to construct the coherency bands, we use returns standardized by their conditional standard deviations, obtained through GARCH models. The models have been estimated for the period 01.04.2020–01.05.2022, comprising several crisis periods. Following Baruník and Kley (2019), we choose to study this long period for several reasons. First, longer than yearly cycles might constitute an important possible source of dependence. Secondly, GARCH models require longer samples (preferably at least 500 observations) to obtain stable results (Hwang & Pereira, 2006).

However, to get more insight into the data, we calculated the coherencies separately for four subperiods, corresponding to different pandemic intensities. We start the coherence analysis in April 2020 to omit the short period of the most extreme downfalls in all markets. The periods of study are:

5 Through standardizing the returns by their volatility, we remove the most critical source of time-variation in data. Unexplained high volatility may seriously bias the analysis of co-dependence between assets (Forbes & Rigobon, 2002).
Table 6
Estimates of volatility models with skewed Student distribution for stablecoins.

| Parameter | Estimate | Std.error | t.stat   | p.value |
|-----------|----------|-----------|----------|---------|
| DAI: ARMA(3,0)-GARCH(1,1) |          |           |          |         |
| $\mu$    | -0.00004 | 0.001     | -0.042   | 0.967   |
| $\alpha$ | -0.547   | 0.060     | -9.098   | <0.001  |
| $\beta$  | -0.358   | 0.079     | -4.561   | <0.001  |
| $\gamma$ | -0.239   | 0.050     | -4.770   | <0.001  |
| $\kappa$ | 0.282    | 0.00002   | 15168    | <0.001  |
| $\nu$    | 0.717    | 0.001     | 517      | <0.001  |
| $\omega$ | 1.073    | 0.062     | 17.264   | <0.001  |
| $\omega$ | 5.492    | 0.831     | 6.609    | <0.001  |
| USD: ARMA(0,1)-GARCH(1,1) |          |           |          |         |
| $\mu$    | -0.0002  | 0.000     | -1.026   | 0.305   |
| $\beta$  | -0.797   | 0.028     | -28.189  | <0.001  |
| $\gamma$ | 0.244    | 0.002     | 152.040  | <0.001  |
| $\nu$    | 0.750    | 0.000     | 2662.882 | <0.001  |
| $\kappa$ | 0.977    | 0.054     | 18.123   | <0.001  |
| $\omega$ | 3.820    | 0.419     | 9.128    | <0.001  |
| $\omega$ | 0.0001   | NA        | NA       | NA      |
| USD: ARMA(1,1)-GARCH(1,1) |          |           |          |         |
| $\mu$    | -0.0001  | 0.001     | -0.181   | 0.856   |
| $\alpha$ | 0.174    | 0.118     | 1.482    | 0.138   |
| $\beta$  | -0.836   | 0.063     | -13.207  | <0.001  |
| $\gamma$ | 0.260    | 0.001     | 266.430  | <0.001  |
| $\nu$    | 0.738    | 0.002     | 382.055  | <0.001  |
| $\kappa$ | 1.239    | 0.056     | 21.970   | <0.001  |
| $\omega$ | 3.773    | 0.219     | 17.249   | <0.001  |
| $\omega$ | 0.0001   | NA        | NA       | NA      |

Note: By $\nu$ we denote the estimated number of the degrees of freedom, and by $\kappa$ — the skewness value in Student distribution. In all the cases we used the variance-targeting option, so the $\omega$ parameter has not been estimated. All the models explained linear and non-linear dependencies in data (according to Ljung-Box test for standardized residuals and ARCH test) and passed Pearson’s goodness of fit test for distribution. We note that the number of degrees of freedom in the Student distribution was lower than 4 in the case of USD and USDT, which signify the extreme kurtosis values. In the case of DAI, all the parameters passed the Nyblom stability test, in the case of Terra $\alpha$, autocorrelation coefficient and $\nu$ were unstable, in the case of USDC: $\alpha$ and $\beta$, and in the case of USDC: $\gamma$ and $\kappa$.

- from April 2020 to the end of August 2020;
- from September 2020 to the end of December 2020;
- from January 2021 to the end of Summer 2021;
- from September 2021 to 23rd of February 2022 — just before the Russian invasion of Ukraine and before the Terra-LUNA crash.

The periods above correspond to the pandemic waves defined in the literature (see e.g. Rothengatter, Zhang, Hayashi, Nosach, Wang, & Oum, 2021) and the pandemic intensity based on the data published by Hale et al. (2021). The first period encompasses the pandemic outbreak, followed by severe stringency measures and fear. In Summer, the precautions have been mostly removed. However, starting from Autumn 2020, the second wave has begun. In 2021, the vaccination campaign has been launched — thus, we begin the third subperiod in January 2021. Eventually, in Autumn 2021, another wave arrived, even more severe, regarding the number of positive cases and deaths. We end the period a day before the Russian invasion of Ukraine, not to introduce another factor that could affect the analysis. In Figs. 3–5 we present the results for common downfalls. We painted the results for traditional safe havens in green, the stablecoins — in blue, and cryptocurrencies — in red.

For clarity, we summarize the results in Table 7. By D! we denote the possibility of extreme downfalls occurring together (positive coherency between the lowest quantiles or negative between the 0.05|0.95 ones), by SH — safe-haven, by WSH — weak safe-haven,

---

6 The authors define three waves of the pandemic:
• 1st wave — from Spring to the end of summer 2020.
• 2nd wave from Fall 2020 to Winter 2020/2021.
• 3rd wave from Winter 2020/2021.
Fig. 2. Estimated conditional standard deviation of S&P 500 (a), US 10-years bonds (b), gold (c), silver (d), Dai (e), Terra (f), Tether (g), USDC (h), ether (i), Bitcoin (j) from April 2020 to September 2021. Note: Returns of traditional safe-havens are painted green, stablecoins — blue, while cryptocurrencies — red.

and by (W)SH — the weak safe-haven with the possibility to obtain extra profit (positive relationship between 0.05|0.95 quantiles). The short period denotes the investment horizon between 2 days and a week, the mid-horizon between a week and a month, and the long — longer than a month.

We observe that the patterns differ depending on the analysed period (and across frequencies). In the first one, corresponding to the first COVID wave, coherency between the returns of precious metals and S&P (Fig. 3(e) and (i)) was insignificantly different from 0, which has made them good candidates for weak safe-havens. The same was true for stablecoins (Fig. 4). As we could have expected – bonds would not have performed such a role – since the coherency for some frequencies was positive (Fig. 3(a)). What is more, we find frequencies for which coherency was negative in the case of BTC (Fig. 5(a)), ETH (Fig. 5(e)), USDC (Fig. 4(i)) and DAI (Fig. 4(a)). For USDC, the coherency was negative for the long-term horizon (longer than a month), for DAI and BTC – for the period around 3–5 days, while for ETH – even longer. Yet, we note that coherency was positive for short-term investment in Bitcoin, which had made such possible protection very unstable. As noted by Maghyereh and Abdoh (2020) - it is more advisable to protect the investment using the index of relatively stable coherency.

Within this period, we find a positive asymmetry between the 0.05|0.95 quantile for S&P-gold (for longer-term investment, around one month), S&P-BTC (for a short-term investment), and S&P-ETH (for the investment of horizon longer than a week). Thus, we can conclude that, at the beginning of the pandemic, the best safe-haven candidates were gold and Ether. Silver and stablecoins could have served as weak safe-havens.

The coherencies were relatively stable in the second subperiod when the pandemics calmed down. Relationships between the extreme downfalls were insignificantly different from 0 for all assets apart from silver (Fig. 3(j)), where it was significantly positive for relatively short-term investment. The short-term investment in T-bonds was also quite risky, as we observed negative relationship between the asymmetric quantiles. Interestingly, in this period, Ether, as the only one, exhibited a negative relationship with S&P for the most extreme lower quantiles. At the same time, the asymmetric relationships were positive for gold and silver for long-term
horizon (Fig. 6(f) and (j)), for stablecoins for long-term (USDT and USDC - Fig. 7(f) and (j)) and mid-term (DAI: Fig. 7(b)) and Bitcoin for short-term horizon (Fig. 8(b)). When we filter out the assets for which the confidence band also covered negative values, we conclude that in the second period, the set of possible safe-havens could have comprised gold, stablecoins, Bitcoin, and Ether.

The third subperiod was characterized by the increased COVID rate but also the start of the vaccination campaign. When we look at the volatility patterns (Fig. 2), we can see that the situation in stablecoin markets has already calmed down. When it comes to the coherencies between the extreme downfalls, we observe that the investment in the traditional safe-havens may not have been profitable for some investment horizons (Fig. 4(c), (g) and (k)). From the cryptocurrencies, only USDC (Fig. 4(k)) and ETH (Fig. 5(g)) did not exhibit positive coherency with S&P downfalls for any frequency (but we observe a negative coherency for the pair S&P-ETH for 0.05|0.95 quantiles). However, there was an opportunity to gain on investment even if S&P fell — due to positive coherency for gold-S&P and Bitcoin-S&P. Yet, since such an investment was rather a risky one, because of the possibility to lose during the periods of joint decreases, we conclude that only USDC could have been a safe safe-haven candidate (see also Table 7, column: Period 3).

Eventually, the last subperiod was relatively stable for the traditional safe-havens (Table 7, column: Period 4). The coherency between the joint declines with S&P was either insignificant or negative, while the asymmetric one was insignificant or positive. Bitcoin could have performed the safe-haven role, while Ether lost such an ability for a shorter-term horizon due to the negative asymmetric relationship with S&P (Fig. 8(h)). From the stablecoins group – only USDT did not exhibit a positive coherency with S&P for the joint extreme declines in any frequency – however, we encounter a negative relationship between the asymmetric quantiles of the assets (Fig. 7(h)). No stablecoin was a perfectly safe investment protection during that time. We can suspect that the market may have already anticipated the crash in the stablecoins market.
To summarize — the safe-haven properties of the assets vary over time (see also Będowska-Sójka and Kliber (2021), Wüstenfeld and Geldner (2022), Selmi, Bouoiyour, and Wohar (2022) and many others). In the first period of the pandemics, the best safe-havens candidates were gold and Ether. In the second one, the centralized stablecoins and Bitcoin could have played such a role, too. In the third one, the set of possible safe-havens shrunk to USDC and ETH. Eventually, in the fourth period, all traditional safe-havens (including bonds) and stablecoins (apart from USDT) could have played safe-haven roles.

5.3. Safe-haven properties of the assets based on the conditional correlation test

As an additional test, we applied the “classical” approach, used i.a. in Baur and Dimpfl (2021), following the remark that the “standard” safe-haven test is more general than asymmetric connectedness. The method examines the expected reaction of the correlation of the base investment with potential safe-haven, conditional on the extreme negative returns of the base asset. Thus, based on the univariate GARCH models, we estimate the DCC model of Engle and Sheppard (2001) in its corrected version of Aielli (2013) and in this way obtain the dynamic conditional correlation between S&P and each possible safe-haven. Next, we estimate a regression model, in which the dynamic conditional correlation is explained by the extreme declines of S&P, i.e.

\[ R_t^{(S&P,SH)} = a_0 + a_1 \cdot D_t^{(S&P \text{ Cap}(0.05))} \]

All the calculations have been performed in R packages rmgarch (Ghalanos, 2019) and xdcclarge (Nakagawa & Imamura, 2018).

Fig. 4. Quantile coherency for extreme downfalls - S&P and stablecoins.
Table 7
Safe-haven properties of the assets — summary of the results.

|                | Period 1 | Period 2 | Period 3 | Period 4 |
|----------------|----------|----------|----------|----------|
|                | short    | mid      | long     | short    | mid      | long     | short    | mid      | long     |
| T-bonds        | D!       | WSH      | D!       | D!       | WSH      | (W)SH    | WSH      | (W)SH    | WSH      |
| gold           | WSH      | (W)SH    | WSH      | (W)SH    | (W)SH    | D!       | D!       | D!       | WSH      |
| silver         | WSH      | WSH      | WSH      | D!       | WSH      | (W)SH    | WSH      | (W)SH    | WSH      |
| DAI            | WSH      | WSH      | WSH      | (W)SH    | WSH      | WSH      | D!       | WSH      | (W)SH    |
| USDC           | WSH      | WSH      | WSH      | WSH      | WSH      | WSH      | WSH      | WSH      | WSH      |
| USDT           | WSH      | WSH      | WSH      | WSH      | WSH      | WSH      | WSH      | D!       | WSH      |
| BTC            | D!       | WSH      | WSH      | (W)SH    | WSH      | WSH      | D!       | WSH      | (W)SH    |
| ETH            | WSH      | SH       | WSH      | WSH      | WSH      | WSH      | D!       | WSH      | (W)SH    |

Note: WSH denotes a weak safe-haven, (W)SH — a weak safe-haven with the possibility to obtain an extra profit (positive relationship between the extreme downfalls of S&P and growth of the second asset, with an insignificant relationship between the lowest quantiles), SH — safe haven (the case when we obtained negative relationship between the lowest quantiles and negative asymmetric relationship), D! — the possibility of joint declines occurring together. The short period denotes the investment horizon between 2 days and a week, the mid-horizon between a week and a month, and the long — longer than a month.

An instrument can be considered a hedge if it is, on average, negatively correlated with S&P ($\alpha_0 < 0$). It can be treated as a safe-haven if its correlation diminishes or becomes negative in the moments of extreme declines in the base asset ($\alpha_1 < 0$). It can be called a diversifier if its correlation with the base asset is, on average, positive ($\alpha_0 > 0$). In this approach, we do not concentrate on the joint distributions of the returns but on the conditional correlation. As noted by Barunik and Kley (2019), there is no simple translation from the quantile coherency to correlation if the distribution of the variables is not Gaussian. In the previous method, we focused on the relationships between extreme returns. Here, we estimate the correlation between the returns (linear relationship) and verify how it behaved in the moments of the extreme negative returns of the base asset (S&P). In Table 8 we provide the results of the estimated coefficients. Grey cells denote that the estimates were insignificant at the 10% level.

We present the estimates for the whole period and in separate subperiods. The best candidate for a hedge would be USDC since, on average, its correlation with S&P was negative all the time. BTC and ETH were the most correlated with S&P (the $\alpha_0$ coefficient exceeded 0.3) and could have served as diversifiers.

However, for some assets, the dependencies changed dynamically, depending on the subperiod. For instance, in the second subperiod, USDT exhibited a small correlation with S&P (0.07), whereas, during the extreme drops of the base asset, the correlation diminished ($\alpha_1$ was significantly negative) — which made the stablecoin a strong safe-haven. In the fourth phase, its correlation with S&P became negative but $\alpha_1$ was insignificant. Thus, the asset became a hedge and a weak safe-haven. In the last subperiod, also gold became negatively correlated with S&P and became a hedge and a weak safe-haven. In all other periods, its correlation with S&P was positive, although very small.
To summarize, according to this test, the best hedge for American stocks were centralized stablecoins and gold. Moreover, USDT performed a strong safe-haven role in the second phase. We also note that $a_1$ was negative but insignificant, for gold, silver, and USDC in all periods, for bonds in the last two periods, for DAI in the first two, and USDT in all periods apart from the third one. That suggests that the correlation diminished during some periods of the downfalls of the S&P and may indicate that the assets could have performed a safe-haven role occasionally during some subperiods. The conclusion requires, however, some deeper investigation.

6. Conclusions

In this paper, we assess the safe-haven properties of selected De-Fi and Ce-Fi stablecoins against the US stocks. To achieve that, we analyse the relationships in quantiles between the S&P and the traditional safe-havens (US T-bonds, gold, and silver) and compare it with the relationships between the S&P and DAI, Tether, and USDC. We use the non-parametric quantile coherency method and estimate the coherency between the returns standardized by volatility obtained using the univariate GARCH models. We concentrate on the relationships in tails.

Since the pandemic has differed in its intensity, we analyse the relationships in subperiods. We find that during the periods of relative pandemic stability, the set of potential safe-havens widened. Yet, the safe-haven properties of the assets differed also across investment horizons. For instance, gold acted as a safe-haven for all-term investments in all the periods, apart from the third one (01.01.2021–31.08.2021), when it was a safe-haven for long-term investment only. On the contrary, silver was a safe-haven for all-term investments in the first and third periods; for mid- and long-term investments in the second one, and for short- and long-term — in the third one. US T-bonds became safe-havens regardless of the investment horizon in the fourth period only.
Fig. 7. Quantile coherency for 0.05/0.95 quantiles - S&P and stablecoins.

We aimed to compare the possible safe-haven properties of “new” safe-havens (cryptocurrencies) with traditional assets (gold, silver, bonds) during the COVID-19 pandemic. We encountered that stablecoins could have served as safe-havens in the first and second pandemic periods, regardless of the investment horizon. In the third subperiod only USDC retained that property, while in the fourth one, the investment became riskier.

To get more insights into the nature of the relationships, we performed an additional test based on dynamic conditional correlation. It shows that some centralized stablecoins could have acted as hedges and strong or weak safe-havens against S&P during the pandemic. The properties of DAI (de-centralized stablecoin) differed from the properties of the USDC and USDT, especially in the third and fourth phases. Yet, its close to zero correlation with the base asset resembled the small correlation of silver rather than the relatively strong ones of Ether and Bitcoin.

6.1. Policy implications and limitations of the study

The results imply that one should carefully choose a potential safe-haven asset, depending on the investment horizon. An asset that acts as a safe-haven in a short-term horizon may exhibit positive asymmetric coherency in the mid- or long-term. The conclusion applies not only to the “new” safe-havens (cryptocurrencies and stablecoins) but to the traditional ones (gold, silver, bonds).

The limitation of the research is that we consider only the most liquid stablecoins. The conclusions could be broadened if we extended our set. On the other hand, including less liquid stablecoins in the portfolio would yield an obvious question about the practical usage of such an asset to protect the investment.

Secondly, we end our analysis just before the Terra–LUNA crash. In May 2022, the stablecoin used to be the fourth-largest one, with 18 billion USD in market capitalization (Briola, Vidal-Tomás, Wang, & Aste, 2022). Analysts identify two main events that
Table 8
Estimates of the safe-haven regression model.

| T-bonds | gold | silver | DAI | USDC | USDT | BTC | ETH |
|---------|------|--------|-----|------|------|-----|-----|
| **Full period** |     |        |     |      |      |     |     |
| \(a_0\) | 0.151 | 0.010  | 0.074 | 0.032 | -0.076 | 0.074 | 0.346 | 0.377 |
| \(a_1\) | 0.032 | -0.011 | -0.005 | -0.014 | -2 \cdot 10^{-6} | -0.017 | 0.005 | 0.051 |
| **First phase: 1.04.2020–31.08.2020** |     |        |     |      |      |     |     |
| \(a_0\) | 0.384 | 0.034  | 0.083 | 0.035 | -0.076 | 0.049 | 0.346 | 0.419 |
| \(a_1\) | 0.048 | -0.007 | -0.007 | -0.015 | 0.000016 | -0.036 | 0.004 | 0.0533 |
| **Second phase: 1.09.2020–31.12.2020** |     |        |     |      |      |     |     |
| \(a_0\) | 0.346 | 0.090  | 0.077 | 0.011 | -0.076 | 0.071 | 0.345 | 0.355 |
| \(a_1\) | 0.063 | -0.022 | -0.010 | -0.008 | -0.00014 | -0.037 | 0.004 | 0.027 |
| **Third phase: 01.01.2021–31.08.2021** |     |        |     |      |      |     |     |
| \(a_0\) | 0.043 | 0.033  | 0.068 | 0.033 | -0.076 | 0.072 | 0.338 | 0.258 |
| \(a_1\) | -0.056 | -0.004 | -0.005 | 0.010 | -6.69 \cdot 10^{-6} | 0.012 | 0.0001 | 0.019 |
| **Fourth phase: 01.09.2021-23.02.2022** |     |        |     |      |      |     |     |
| \(a_0\) | 0.164 | -0.031 | 0.094 | 0.046 | -0.076 | -0.002 | 0.351 | 0.451 |
| \(a_1\) | 0.057 | -0.016 | -0.027 | 0.021 | -0.00002 | -0.027 | 0.0001 | 0.011 |

Note: in the table, we provide estimates of the regression: \(R_{S&P,S_H}^{S\&S_H} = a_0 + a_1 \cdot D_{S&P<0.05}(t)\), where \(R\) denotes conditional correlation between S&P and possible safe-haven (\(S_H\)) asset. The grey cells denote insignificant estimates at 10% level. The instrument can be considered a hedge if the intercept \(a_0\) is negative, while a strong safe-haven when \(a_1\) is significantly lower than 0.

stayed behind the Terra collapse. First, some speculators intentionally short-sold Bitcoin to spread panic into the market (after Briola et al., 2022). Secondly, the Terra–LUNA suffered a series of “liquidity pool attacks” in May 2022 and, despite the attempts of the Terra Team to improve the mechanisms of burning and minting Terra–LUNA, both tokens eventually collapsed on 13 May 2022.

The failure of the Terra project represents further evidence of the fragility of algorithmic stablecoins (see also Clements, 2021). Our analysis shows the potential of stablecoins – especially the centralized ones – to protect the investment during turbulences. However, the Terra–LUNA case illustrates a constant need to improve the algorithmic protocols of the De-Fi stablecoins to assure
Table 9
Information on data preparation — merging data of different lengths (data period: 01.04.2020–01.05.2022).

| Series         | SPX | US bonds | Gold | Silver | Cryptos |
|---------------|-----|----------|------|--------|---------|
| Initial length| 761 | 761      | 761  | 761    | 761     |
| Number of na’s| 236 | 239      | 240  | 236    | 0       |
| Final length  | 507 | 507      | 507  | 507    | 507     |
| obs.deleted  | 18  | 15       | 14   | 18     | 254     |

Table 10
Descriptive statistics of the returns calculated for data with missing informations interpolated.

|                          | Mean  | Sd    | Min  | Max   | Kurtosis | Skewness |
|--------------------------|-------|-------|------|-------|----------|----------|
| Base asset               |       |       |      |       |          |          |
| SPX                      | 0.068 | 0.883 | −6.075 | 3.349 | 8.311 | −0.731    |
| Traditional safe havens  |       |       |      |       |          |          |
| USbonds                  | 0.202 | 2.954 | −18.760 | 13.353 | 8.388 | −0.350    |
| gold                     | 0.025 | 0.784 | −5.265 | 3.490 | 8.922 | −0.843    |
| silver                   | 0.068 | 1.535 | −9.139 | 10.209 | 11.623 | 0.101     |
| DEFI stablecoins         |       |       |      |       |          |          |
| terra                    | 0.835 | 8.256 | −48.760 | 64.139 | 12.492 | 0.765     |
| DAI                      | −0.003 | 0.522 | −3.039 | 4.080 | 17.262 | 0.756     |
| CEFI stablecoins         |       |       |      |       |          |          |
| USDC                     | 0.001 | 0.166 | −1.035 | 1.239 | 16.518 | 0.380     |
| USDT                     | −0.001 | 0.214 | −1.899 | 1.692 | 29.092 | −0.770    |
| Cryptocurrencies         |       |       |      |       |          |          |
| BTC                      | 0.232 | 3.641 | −14.811 | 17.182 | 5.334 | −0.041    |
| ETH                      | 0.399 | 4.842 | −31.746 | 23.070 | 7.308 | −0.380    |

their reliability and stability. Some authors warn that the underlying algorithms of such stablecoins lack transparency, prudential safeguards, and supervision (Clements, 2021). Therefore, the results of our study should be interpreted with caution. Similar to the case of all cryptocurrencies, there remains an open question of whether such safe-havens are indeed safe.

CRediT authorship contribution statement

Agata Kliber: Conceptualization, Methodology, Data curation, Data analysis, Writing – original draft, Visualization, Investigation, Writing – reviewing and editing.

Data availability

Data will be made available on request.

Appendix A. Information on data preparation

See Table 9.

Appendix B. Descriptive statistics of data with missing observations interpolated

See Table 10.

References

Ahmed, M. Y., & Sarkodie, S. A. (2021). COVID-19 pandemic and economic policy uncertainty regimes affect commodity market volatility. Resources Policy, 74, Article 102303. http://dx.doi.org/10.1016/j.resourpol.2021.102303, URL: https://www.sciencedirect.com/science/article/pii/S0301420721003135.

Aielli, G. P. (2013). Dynamic conditional correlation: On properties and estimation. Journal of Business & Economic Statistics, 31(3), 282–299. http://dx.doi.org/10.1080/07350015.2013.771027, arXiv:https://doi.org/10.1080/07350015.2013.771027.

Andrieş, A. M., Ongena, S., & Sprincean, N. (2021). The COVID-19 pandemic and sovereign bond risk. The North American Journal of Economics and Finance, 58, Article 101527. http://dx.doi.org/10.1016/j.najef.2021.101527, URL: https://www.sciencedirect.com/science/article/pii/S1062940821001431.

Aramonte, S., Huang, W., & Schrimpf, A. (2021). DeFi risks and the decentralisation illusion. In Quarterly review. Bank for International Settlements, URL: https://www.bis.org/publ/qtrpdf/r_qt2112b.htm.

Barunik, J., & Kley, T. (2019). Quantile coherency: A general measure for dependence between cyclical economic variables. The Econometrics Journal, 22(2), 131–152. http://dx.doi.org/10.1093/ejct/utz002, arXiv:https://academic.oup.com/ejct/article-pdf/22/2/131/37967341/utz002_online_appendix.pdf.

Baumöhl, E. (2019). Are cryptocurrencies connected to forex? A quantile cross-spectral approach. Finance Research Letters, 29, 363–372. http://dx.doi.org/10.1016/j.frl.2018.09.002, URL: https://www.sciencedirect.com/science/article/pii/S1544612318305611.

Baumöhl, E., & Vyrost, T. (2020). Stablecoins as a crypto safe haven? Not all of them! ZBW · Leibniz Information Centre for Economics, EconStor Preprints(215484), URL: https://ideas.repec.org/p/zbw/escpr/p/215484.html.

Baur, D. G., & Dimpfl, T. (2021). A safe haven index. Available at SSRN 3641589.

Baur, D. G., & Hoang, L. T. (2021). A crypto safe haven against Bitcoin. Finance Research Letters, 38, Article 101431. http://dx.doi.org/10.1016/j.frl.2020.101431, URL: https://www.sciencedirect.com/science/article/pii/S1544612319312632.
