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When you need them, they are not there: hedge capacities of cryptocurrencies disappear in downtrend markets

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Abstract

We provide empirical evidence supporting the economic reasoning behind the impossibility of diversification benefits and the hedge attributes of cryptocurrencies remaining in force during the downside trends observed in bearish financial markets. We employ a spillover connectedness model driven by time-varying parameter vector autoregressions on daily data covering January 2018 to November 2022 to analyze spillover transmissions between conventional and digital markets, focusing on the role of stablecoin issuances. We study the stock, bond, cryptocurrency, and stablecoin markets and find very high connectedness, which varies over time in response to up/down trends in financial markets. The results show that during financial turmoil, cryptocurrencies amplify downside risks rather than serve as diversifiers. In addition to risky assets from conventional financial markets, cryptocurrencies champion the transmission of spillovers to digital and conventional markets. In contrast, changes in stablecoin issuances produce few shocks because of their pegged prices, but they facilitate investors' switch from volatile cryptos to more stable digital instruments; that is, we observe a phenomenon designated by us as the "flight-to-cryptosafety." We draw insightful conclusions, provoking new thinking regarding portfolio hedge strategies that could potentially benefit investors when searching for less volatile investment performance.

Highlights

- Connectedness among stocks, the US Treasuries, cryptos, and stablecoins is analyzed
- High connectedness exists due to stablecoin issuances
- Cryptos amplify downside risks and are not diversifiers in extreme market trends
- Stablecoins facilitate the flight-to-safety and flight-to-cryptosafety phenomena
- Stablecoin issuances are a potential hedge signal for large scale and institutional investors

Keywords: Stablecoins, Stocks, Cryptocurrencies, Bitcoin, US treasuries, Digital financial market, Conventional financial market, Flight-to-cryptosafety, Flight-to-safety, TVP-VAR model

JEL Classification: C32, E42, F31, G1, G2, G12

Introduction

The phenomenal growth of digital assets, predominately cryptocurrencies, is attributed to several benefits offered to investors and other participants in various financial markets. Cryptocurrencies aid investors in executing transactions remotely without passing through financial institutions. This decentralization system, operated by cryptocurrencies, ensures user independence, flexibility, and constant accessibility (Grobys et al. 2021). Because of these attractive features, investments in cryptocurrencies appeal to several investors, increasing their willingness to commit funds to them (Wang et al. 2020). However, given the radical volatility of cryptocurrency prices and/or returns, investors with a high level of risk aversion are hesitant to include cryptocurrencies in their portfolios. Harvey (2014) reports that the volatility of Bitcoin is over eight times higher than the overall stock market. Recent evidence obtained by Corbet et al. (2018) and Smales (2019) is consistent with that of Harvey (2014). Furthermore, Baur and Hoang (2021) indicate that price volatility in the Bitcoin market not only manifests in the long term, but is also significant on a daily basis. These attributes of Bitcoin, in particular, and cryptocurrencies, in general, make it challenging for investors to record stable returns or even maintain the worth of their investments.

Stablecoins were introduced to withstand the absence of stability in the returns of traditional cryptocurrencies. Being less volatile surrogates of traditional cryptocurrencies, stablecoins are designed to be price-stable cryptocurrencies whose value is pegged against conventional safe assets, such as commodities (in particular, precious metals such as gold and silver) and fiat currencies (e.g., the US Dollar and the Chinese Yuan). The network between decentralized vaults and commodity traders makes stablecoins more decentralized—a feature that makes them highly attractive to cryptocurrency investors (Wang et al. 2020).

The use of safe assets from traditional financial markets to collateralize stablecoins, which are intended to be safer substitutes for traditional cryptos, suggests that the link between stablecoins and cryptocurrencies extends not only to individual safe assets, such as fiat currencies and commodities, but also to other assets, such as US Treasuries and Commercial Paper, which have more direct links with stocks and bonds from traditional financial markets. For instance, Kim (2022) finds that on a given day, a unit standard deviation rise in stablecoin issuances (in particular, for Tether and USD Coin), amounting to $330 m, drives a 11% rise in the next day's issuance of short-term-maturity Commercial Paper, with an 18(15) basis point drop in the Commercial Paper (US Treasury) yield.

Against this backdrop, we argue that since the "stability" of stablecoins is rooted in investors' belief that the reliable fiat currencies and/or other traditional safe assets back stablecoins, new issuances of stablecoins imply the acquisition, by the issuing entity, of ideally an equivalent amount of conventional safe assets, increasing the demand for "risk-free" securities and reducing risk-free interest rates. In turn, decreasing risk-free rates signal that investors are likely to be more concerned about the performance of risky assets (Gubareva and Borges 2016; Gubareva and Umar 2023; Bossman et al.

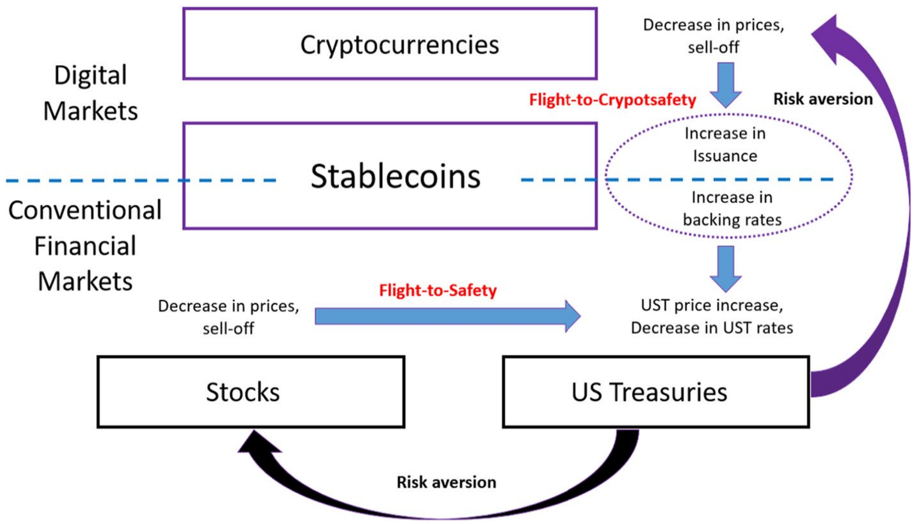

Fig. 1 Flight-to-safety (financial markets) and flight-to-cryptosafety (digital markets)

2022a; Gubareva et al. 2023a, b; Klement 2022). Hence, such decreases in risk-free rates cause other investors from both digital and digital-averse conventional markets to sell risky assets, such as stocks. Therefore, the shift in investors' preferences from cryptocurrencies to stablecoins provides markets with a hint of generalized risk aversion, thereby triggering sell-offs of conventional risky assets, such as equities. Accordingly, we argue that no cryptocurrencies are supposed to be uncorrelated with stocks during market downturns and, consequently, they are not supposed to diversify, but, on the contrary, amplify downside risks.

The dynamics among stablecoins, traditional cryptocurrencies, treasuries, and the stock markets discussed above are visualized in the flowchart in Fig. 1.

The flight-to-safety and flight-to-cryptosafety phenomena are shown in Fig. 1. Here, given that in periods of price decay in conventional financial markets, the switch from stocks to Treasuries can be classified as a flight-to-safety (Bossman et al. 2022a; Gubareva et al. 2023a, b), we designate the switch from conventional cryptos to stablecoins as the "flight-to-cryptosafety" (Gubareva et al. 2023a). The essence of the flight-to-cryptosafety phenomenon resides in the flight of crypto investments from the high volatility and relative instability of conventional cryptos to safer crypto instruments, namely, stablecoins, which are less volatile and comparatively stable.

From our prior argument, stating that no cryptocurrencies are supposed to be uncorrelated with stocks during market downturns and, consequently, they are not supposed to diversify but, on the contrary, amplify the downside risks, we hypothesize that during pronounced downmarket trends, the alleged diversification attribute of traditional cryptocurrencies vanishes, and the only digital asset that ensures stable returns and maintains the value of investments for investors is stablecoins. These specially designed digital coins, pegged against conventional fiat currencies and/or precious metals, facilitate a switch in digital investments from riskier conventional cryptos to safer and more stable instruments without exiting the digital realm. Amid the relative stability of stablecoins over cryptocurrencies and given the significant interdependence dynamics between stablecoin issuances and demand for safe assets from conventional financial markets, we hypothesize that the collective growth in stablecoin issuances, when envisaged as an investment choice, offers a crypto hedge and safe haven for cryptocurrencies. In turn, increasing demand for conventional safe assets results in an increase in safe asset prices, that is, in a decrease in their yields, making safe assets eventually outperform traditional risky assets such as stocks. Therefore, conventional investors may start transferring from the riskiness of stocks to the safety of US Treasuries, further intensifying the vicious circle of flight-to-safety in the realm of conventional financial markets.

Based on the above discussion, we summarize the following objective-driven hypotheses:

> *H_1: Cryptocurrencies bear high connectivity with conventional assets and amplify downside risks in crisis periods.*
> *H2: Stablecoins reduce downside risks during pronounced market downturns, facilitating the link between traditional and digital asset investments.*
> *H3: Investment-wise, the collective growth in stablecoin issuances offers a crypto hedge.*

To test our hypotheses, we investigate the dynamics of spillover connectedness among stablecoin issuances, cryptocurrencies, stocks, and treasuries. Information on the connectedness between markets is important for allocating assets and managing risks (Agyei et al. 2023; Bossman et al. 2023). This is particularly important for investors and portfolio managers who, in various market trends, need to consider the transmission of spillovers and the propagation of contagion between assets to make effective decisions.

Theoretically, consistent with portfolio selection, as emphasized by Markowitz's (1952) modern portfolio theory, the volume of risk propagated by an asset to a portfolio must be outweighed by the volume of returns it contributes to that portfolio. Hence, in market downtrend periods, nominally rational, but practically irrational, investors are motivated to relentlessly explore the diversification and safe-haven potential of various assets. The hastiness of these investors to land on specific assets whose return contributions to a portfolio outweigh the risks they possess induces cross-asset or cross-market shock transmission, given that various assets (markets) may possess varied efficiency levels (Bossman et al. 2023). This situation highlights the relevance of the competitive markets theory (hypothesis), which explains why spillover transmission between multiple assets (markets) intensifies during market downtrends (Owusu Junior et al. 2021). Therefore, against the backdrop of the popularity of digital asset investment in recent years, we anticipate direct links shared by stablecoins, cryptocurrencies, fiat currencies, commodities, and other traditional financial assets, such as US Treasuries and Commercial Paper (Kim 2022). In addition, we suspect that the diversification and safe haven attributes of crypto assets, vis-à-vis other assets from conventional markets, possess a time-varying nature. This theory supports our investigation of the connectedness between cryptocurrency, stablecoin, treasuries, and stock markets.

Empirically, we acknowledge the existence of two major strands of literature, in which we establish a void that we seek to fill. The first strand covers crypto-based studies, probing the safe haven and hedge attributes of cryptocurrencies. For instance, some studies ascertain Bitcoin's position in a system of conventional assets, such as stocks (Bahloul et al. 2021; Bouri et al. 2020, 2022), and commodities (Selmi et al. 2018; Shahzad et al. 2019; Syuhada et al. 2022). Others also explore the resilience of cryptos to market stress (Bouri et al. 2018), policy uncertainty (Hasan et al. 2022), and the connection between cryptos in the face of cryptovolatility (Agyei et al. 2022a). More recently, owing to the widespread use of cryptos in diverse portfolios despite their high volatility, Nedved and Kristoufek (2023) test the safe haven ability of assets from the conventional financial market against cryptos. Their work pioneers focus on scrutinizing the diversification and safe haven attributes of different assets against cryptocurrencies.

The second strand tests stablecoins' influence on conventional financial markets. Here, the main themes covered by the extant literature include how stablecoins reduce exchange rate volatility (Giudici et al. 2022), the hedge, diversifier, and safe haven roles of stablecoins vis-à-vis cryptos (Wang et al. 2020; Baur and Hoang 2021), and the stability features of stablecoins (Grobys et al. 2021; Kristoufek 2021; Duan and Urquhart 2023). Similarly, other studies analyze the causal links between stablecoin issuances and crypto market volatility (Wei 2018; Ante et al. 2021). Out of the stablecoin-based papers, Nguyen et al. (2022) champion a frontier strand of stablecoin literature by documenting a link between interbank rates and stablecoin trading volumes. This highlights the work of Gubareva et al. (2023a), who scrutinize the role of stablecoins in bridging conventional and digital financial markets. However, this study does not ascertain whether, in the presence of stablecoins, the hedge capacities of conventional cryptocurrencies vis-à-vis traditional financial assets remain during market downtrends considering the spillover dynamics between the markets.

To the best of our knowledge, the existing literature on stablecoins has yet to show that the hedge capacities of cryptos are missing in downtrends in the market. Despite the intuitive mechanism underlying the interrelations between stablecoin issuances, treasuries, and the dynamics of stock markets, our study provides relevant contributions to the literature by scrutinizing the hedge attributes of cryptocurrencies in light of the influence of stablecoins on financial markets, jointly considering the two aforementioned strands of work and linking them together. The presence of stablecoins backed by fiat currencies in the linkage between the assets from the conventional and digital markets is important because of the dual essence of such stablecoins, which, from one perspective, are digital instruments traded at crypto exchanges, whereas, in contrast, they may affect traditional financial markets through the demand for safe assets needed to back these stablecoins. Notably, stablecoins reside in the practicality of envisaging them as links between traditional and digital financial markets. Our vision is based on the fact that (1) stability is rooted in the stability of underlying assets, which is derived from traditional financial markets. Moreover, (2) investment-wise movements in stablecoin issuances may present diversification and safe haven potential, as these digital instruments facilitate the switch from risky conventional cryptos such as Bitcoin to more stable digital assets such as coins backed by fiat currencies. To support our argument, we probe the connectedness and spillover transmission among the cryptocurrency, stablecoin, treasury, and stock markets.

In this study, an analysis of the spillover transmission between various assets—whether digital (cryptocurrencies and stablecoins) or traditional (stocks and treasuries)—is not only essential but also timely due to the phenomenal growth of digital assets, despite their intense volatility, in the financial market landscape. This study makes the following significant contributions to the literature:

First, cryptos are gradually becoming a standard component in the portfolios of both individual and institutional investors. Therefore, protecting against the extreme trends of cryptos and diversifying (and hedging) their associated risks are two essential factors that investors must consider when making decisions concerning asset allocation and risk management. Hence, investigating the connectedness among stablecoins, conventional cryptos, and major asset classes in conventional financial markets is important to facilitate portfolio management.

Second, we provide empirical evidence of the feasibility of stablecoins as drivers of connectedness between the digital and conventional financial markets, thereby extending the frontier field pioneered by Gubareva et al. (2023a). It should be noted that stablecoin issuances do not transmit shocks to other assets in major extreme market trends, or vice versa; this has important implications for various market players. For instance, changes in issuances and the capitalization of stablecoins may be an important signal for market traders and regulators to line up actions against possible market stress in the future. In this case, institutional investors with comparatively large allocation sizes for various assets may benefit from stablecoins as a possible hedge or safe haven against volatile (risky) crypto investments.

Third, in the framework of our analysis, instead of a single stablecoin, we also employ the ABMG (Ahmed Bossman Mariya Gubareva) Index, which comprises the eight most capitalized stablecoins. By doing so, we test whether, in demonstrating their "stability," basket-based stablecoins outperform their counterparts hinged on single currencies, as Giudici et al. (2022) underscore. From the perspective of issuances, we find that the behavior portrayed by the ABMG Index is qualitatively similar to the dynamics of individual stablecoins, such as Tether.

Fourth, we add to the embryonic strand of the literature by focusing on how stablecoins interact with conventional cryptos and assets from conventional financial markets. We add to emerging works that incorporate several assets into analysis of the stability property of stablecoins while testing the resilience of cryptos as a hedge in market downtrend periods. Our analysis shows that compared to traditional cryptos, the stablecoin market is embryonic and, hence, amid several other assets from conventional and digital financial markets, its stability (and, for that matter, the position of various stablecoins as net receivers of innovations from traditional and other digital markets) is driven by the fact that it is an emerging market. Thus, it is comprehensible that in the transmission of risk and propagation of shocks, a relatively emerging market such as the stablecoin will receive shocks from its relatively developed counterparts in both conventional and digital financial markets (Agyei et al. 2022b; Li et al. 2023).

It is worth explaining in more detail the concepts of stablecoins and traditional cryptocurrencies, along with their fundamental characteristics. Stablecoins are cryptos whose value is tied to the value of another currency, commodity, or other financial asset (Fiedler and Ante 2023). Stablecoins offer an alternative to popular conventional cryptocurrencies, which are characterized by high price volatility, making them less appropriate for common transactions (Wang et al. 2020; Nguyen et al.

2022). Stablecoins are cryptos that attempt to tie their value to an external benchmark. Thus, stablecoins are more useful as a medium of exchange than are conventional volatile cryptos. In particular, much attention has been paid to stablecoins pegged to the USD or gold (Fiedler and Ante 2023; Gubareva et al. 2023a; Ali et al. 2024). The taxonomy of different kinds of stablecoins may be represented by the following: traditional asset-backed stablecoins, crypto-collateralized stablecoins, algorithmic stablecoins, and seigniorage shares. These features are the criteria considered when assessing a stablecoin. Regarding conventional cryptocurrencies in general, a cryptocurrency is a digital instrument based on a network that is distributed across a large number of computers. This decentralized structure allows them to exist outside the control of governments and central authorities. One advantage of cryptocurrencies is that decentralized systems do not collapse at a single point of failure. Among the disadvantages of conventional cryptos are their elevated price volatility, high energy consumption for mining activities, and use in criminal activities. Cryptocurrency is a virtual currency secured by cryptography, which makes counterfeiting nearly impossible. However, because the crypto landscape represents a symbiosis between conventional cryptocurrencies and stablecoins, it is highly desirable to study their interconnectedness to provide crypto investors with actionable knowledge.

Methodologically, we chose the spillover connectedness metric of Antonakakis et al. (2020), i.e., the connectedness approach based on time-varying parameter vector autoregressions (TVP-VAR). This approach extends the basic connectedness measure of Diebold and Yilmaz (2014) by allowing flexibility in the variance–covariance matrix through the application of Koop and Korobilis's (2014) Kalman filter method. Hence, the TVP-VAR connectedness measure allows us to ascertain the overall connectedness between a system of intended variables in both the averaged (static) and time-varying terms. Regarding time-varying connectedness, the TVP-VAR spillover metric yields robust results without loss of observations, as may be the case in an alternative approach, such as the connectedness metric of Baruník and Křehlík (2018).

To the best of our knowledge, this is the first study to use the TVP-VAR connectedness approach to analyze the connectivity of stablecoins with financial markets. As we can envisage the evolution of connectedness between the variables in the intended system using this method, other approaches, such as biwavelet analysis and ordinary least squares, may not satisfy our aim. Our selected approach helps us infer the magnitude of spillovers and sources of contagion between conventional and digital financial markets. We show that during pronounced market downtrends, (1) cross-market connectedness is high between conventional and digital financial markets; (2) stock markets, treasuries, and traditional cryptocurrencies are propagators of shocks to the stablecoin market; (3) the hedge capacities of traditional cryptocurrencies disappear at extreme trends in markets; and (4) stablecoin issuances, serving as a signal for investors, facilitate the switch from risky cryptocurrencies to their more stable counterparts—a condition that substantiates the flight-to-cryptosafety.

The remainder of this paper is organized as follows. "Literature review" section presents a synthesis of the existing literature. "Data and econometric framework" section describes our data and econometric approaches. We discuss the empirical results in

"Empirical results" section and provide concluding remarks in "Concluding remarks" section.

Literature review

Theoretical basis

The theoretical framework guiding our analysis is anchored in theory of financial contagion and competitive markets. Amid the plethora of definitions of contagion, we particularly highlight the conceptualization proposed by Forbes and Rigobon (2001, 2002). From this perspective, the evolution of interconnectedness among financial markets or assets is designated as interdependent if there is no substantial alteration in the connectivity pattern following the onset of a crisis in one or a group of markets or assets. Conversely, if a marked distortion in the interconnectedness pattern is observed, the linkage is ascribed to contagion, with its origin traced back to the market or assets from which the crisis originated. Within this framework, we delve into the nature of connectedness among cryptocurrencies, stablecoins, treasuries, and stocks, examining how such connections respond to significant events—specifically, market upturns and downturns—in any of these markets. This exploration allows us to discern whether the observed connectedness arises from interdependence or contagion.

Competitive market theory accentuates the phenomenon that during crises, cross-market connectedness experiences notable amplifications, attributable to the rush among nominally rational yet potentially irrational investors for safe assets (Owusu Junior et al. 2021). Against this backdrop, we acknowledge that the competitiveness of investment choices among cryptocurrencies, stablecoins, treasuries, and stocksis anticipated to intensify during market upturns or downturns, and is potentially linked to financial contagion. Thus, the efficacy of competitive trading strategies employed by investors in extreme market conditions may hinge on the historical connectivity trends between these markets. This underscores our motivation to evaluate whether the diversification benefits and hedging attributes of stablecoins, cryptocurrencies, treasuries, and stocks persist during the downside trends observed in bearish financial markets. This analysis contributes to the literature on the interdependence structure between diverse financial markets across various contexts, such as the commodity-equity nexus (Bossman and Agyei 2022), stock–bond nexus (Gubareva and Borges 2016; Gubareva et al. 2023a, b), and developed-versus-developing market nexus (Heliodoro et al. 2020).

Background literature

It is important to mention that we acknowledge that several studies focus on testing the hedge, diversification, and safe haven attributes of cryptocurrencies, primarily Bitcoin (Agyei et al. 2022a; Bahloul et al. 2021; Bouri et al. 2018, 2020, 2022; Conlon and McGee 2020; Umar and Gubareva 2020; Hasan et al. 2022; Nedved and Kristoufek 2022; Selmi et al. 2018; Shahzad et al. 2019; Syuhada et al. 2022; Kumar et al. 2023; Mensi et al. 2023; Yousaf et al. 2022, 2023; Mensi et al. 2024). Hence, we distinguish our work by associating it with the strand of literature that not only assesses the resilience of cryptos as diversifiers, safe havens, or hedges for traditional assets, but also addresses the interdependence of the diversification and hedging attributes of crypto assets with those of stablecoins. In tandem with our analytical framework, our study aligns with existing literature that underscores the role of cryptocurrencies (excluding stablecoins) in equity markets (Jana et al. 2023; Jana and Sahu 2023a, 2023b), particularly in comparison with traditional safe assets such as precious metals and benchmark stocks (Kyriazis et al. 2023; Sharma and Karmakar 2023). Our distinctive contribution to this body of research lies in our thorough examination and documentation of the interdependence between cryptocurrencies and stablecoins juxtaposed with the US treasury and stock markets. This nuanced exploration provides a comprehensive perspective on the intricate relationships within this financial landscape, enriching existing discourse on the dynamic interactions between digital and conventional assets.

In the COVID-19 era, Będowska-Sójka and Kliber (2022) analyze whether major digital currencies hedge against oil price volatilities and find that stablecoins are the best hedging and safe-haven candidates for oil and cryptocurrency investment portfolios. Wang et al. (2020) test the hedging, diversification, and safe-haven attributes of stablecoins against conventional cryptocurrencies. They emphasize that the ability of stablecoins to act as safe havens depends on market conditions. Ghabri et al. (2022) assess the information transfer between oil, cryptos, and stablecoins using a transfer entropy metric. The results highlight a change in the patterns of information transfer between these markets owing to the COVID-19 pandemic.

Furthermore, Baur and Hoang (2021) document that stablecoins serve as strong safe havens for Bitcoin. They further advance that due to the responsiveness of stablecoins to Bitcoin price changes, the stability of stablecoins is condition-dependent, lending support to Wang et al.'s (2020) conclusion. Ante et al. (2021) explore how various issuances of stablecoins influence cryptocurrencies using an event study framework and report that stablecoin issuances result in price discovery and market efficiency for cryptocurrencies. Kristoufek (2021) find no evidence suggesting that stablecoin issuances affect cryptocurrency prices. Instead, the findings suggest that stablecoin issuances follow crypto market price hikes, an observation that is consistent with Grobys et al. (2021). Duan and Urquhart (2023) provide evidence of instability among stablecoins and support to the findings of Kristoufek (2021) and Grobys et al. (2021). In explaining the relationship between stablecoin issuances and the pricing and return-generating processes of traditional cryptos, Wei (2018) shows that there is no evidence to support a causal relationship between the issuance of ether stablecoins and bitcoin returns. However, a causal relationship exists between stablecoin and Bitcoin trading volumes.

Assessing the capacity of stablecoins to mitigate foreign exchange volatility spillovers, Giudici et al. (2022) compare the value-preservation ability of basket-based and single-currency-based stablecoins and find that, in terms of value, basket-based stablecoins are more preservative than their single-currency-based counterparts during market stress. Moreover, they document the ability of the analyzed stablecoins to maintain orthogonality to the dynamics of the considered fiat currencies; therefore, their results corroborate the thesis of the stability of stablecoins.

Nguyen et al. (2022) test the responsiveness of stablecoins and conventional cryptos to interbank rates in the US and China. The results show a negative (positive) connection between the prices and the volatility of stablecoins (conventional cryptos) and interbank rates. However, in terms of trading volumes, both assets respond positively to interbank rates. Other studies assess the main events in stablecoin markets. For instance, Briola et al. (2023) account for the failed Terra-Luna Stablecoin Project. Gadzinski et al. (2022) define various categories of stablecoins based on architectural design and test their linkages with their pricing.

Motivation

Studies examining the connection between stablecoins and financial markets have yet to explore the dynamics of spillover transmission and propagation. Our analysis fills this gap in the literature because the dynamics of connectedness between various assets (markets) serve as important tools for evaluating portfolios and policy decisions (Agyei et al. 2022b; Diebold et al. 2017; Owusu Junior et al. 2022; Umar et al. 2021). Existing studies lack an empirical evidence-based understanding of the interactions between stablecoins and various assets from both digital and conventional financial markets. In particular, there is no evidence of linkages between stablecoins, traditional cryptocurrencies, stocks, and US treasuries.

Our analysis is motivated by (1) the rapid growth of digital currencies and (2) the direct and indirect links between the named markets, as aroused by the issuance of stablecoins (Kim 2022). Therefore, we analyze the evolution of connectedness between digital and conventional financial assets. Given that the cryptocurrency market is driven by volatility (Bouri et al. 2022; Ren and Lucey 2022), we expect Bitcoin and other traditional cryptocurrencies in our sample to be the main transmitters of spillovers to conventional financial assets such as stocks. Accordingly, given the relative "stable" property of stablecoins, we do not expect stablecoin issuances to be the main transmitters of shocks to other assets. Overall, the foundation for our analysis is the ability of stablecoins to drive the connection between conventional and digital financial markets through the flight-to-safety and flight-to-cryptosafety phenomena, especially during periods of price decay, as exhibited by extreme market trends.

Data and econometric framework

Data metrics

We analyze the dynamics of connectedness between the conventional and digital financial markets. This subsection describes the data in our sample. We employ USD-dominated daily data covering the period from January 05, 2018, to November 10, 2022. For conventional financial markets, we employ stocks (S&P 500 Index (SPX500)) and the US Treasury (proxied by the total return index (ITRROV)). For digital financial markets, we employ traditional cryptocurrencies (Bitcoin (BTC), the Bloomberg Galaxy Crypto Index (BGCI), Ethereum (ETH), and Bitcoin USD cross (XBTUSD)) and stablecoins (the ABMG Index,[1] Tether (USDT), and TetherETH (USD_ETH)). We source data on stablecoins from Coinmetrics and all other data from Bloomberg. We explain our choice of stocks and cryptocurrencies as follows. Regarding the selection of the Standard &

[1] The ABMG index comprises eight major coins: Tether (USDT), TetherETH (USDT_ETH), TetherTRON (USDT_TRX), BinanceUSD (BUSD), Dai (DAI), Gemini Dollar (GUSD), Paxos Standard (PAX), and USD coin (USDC).

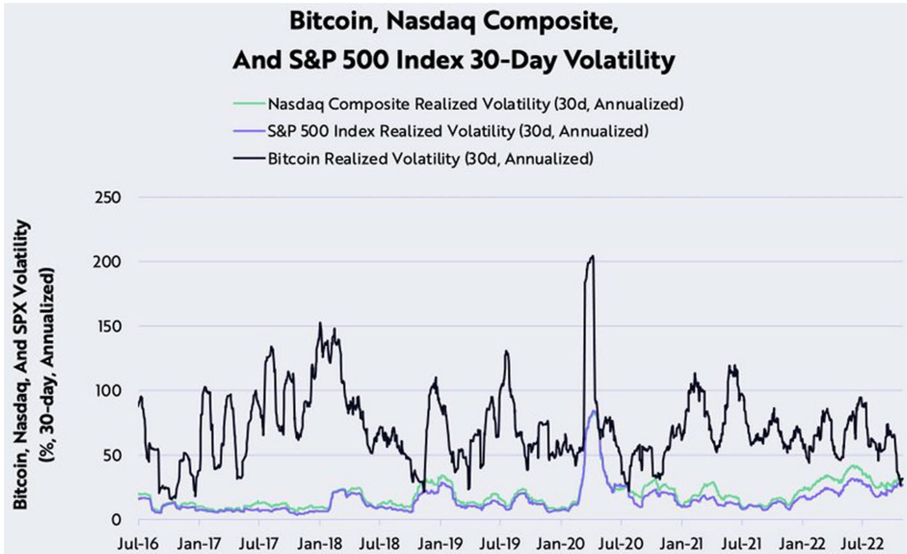

Fig. 2 Trends in market volatility for Bitcoin, Nasdaq, and S&P 500

Poor's 500 Index (S&P 500), we consider that the S&P 500 is one of the most widely used benchmarks for assessing the state of the overall economy, representing a well-regarded reference for the US equity market. In addition, institutional and retail investors, as a rule, use the S&P 500 as a benchmark for their investment portfolios. The S&P 500 comprises 500 large-cap companies across diverse sectors of economic activity; hence, it adequately captures the pulse of the American corporate economy. Our selection criteria for the chosen stablecoins are based on factors such as market capitalization and daily trading volume in the US. Moreover, the member constituents of the ABMG Index are defined by the exclusion criterion of the unavailability of historical data series over the period of the study (Gubareva et al. 2023a). With respect to the conventional cryptocurrencies investigated, our choices are the BGCI (Bloomberg Galaxy Crypto Index), BTC (Bitcoin), ETH (Ethereum), and XBTUSD. Our rationale is as follows. The Bloomberg Galaxy Crypto Index (BGCI) is a commonly used benchmark for the crypto market, designed to measure the performance of the largest cryptocurrencies traded in USD; see, inter alia, Umar and Gubareva (2020). BTC and ETH are the two largest cryptocurrencies in terms of market capitalization. As of December 18, 2023, their approximate market caps were USD 815 billion and USD 260 billion, respectively, according to https://coinmarketcap.com. XBTUSD represents a certain interest as it is known as a cryptocurrency contract-for-difference (CFD) because it is also linked to its base currency, Bitcoin.

The sample described above was determined using the largest matching data available at the time of the study preparation. To understand the importance of possible data length mismatches based on varied numbers of trading days, we followed the conventional practice of maintaining common observations on common trading days for the

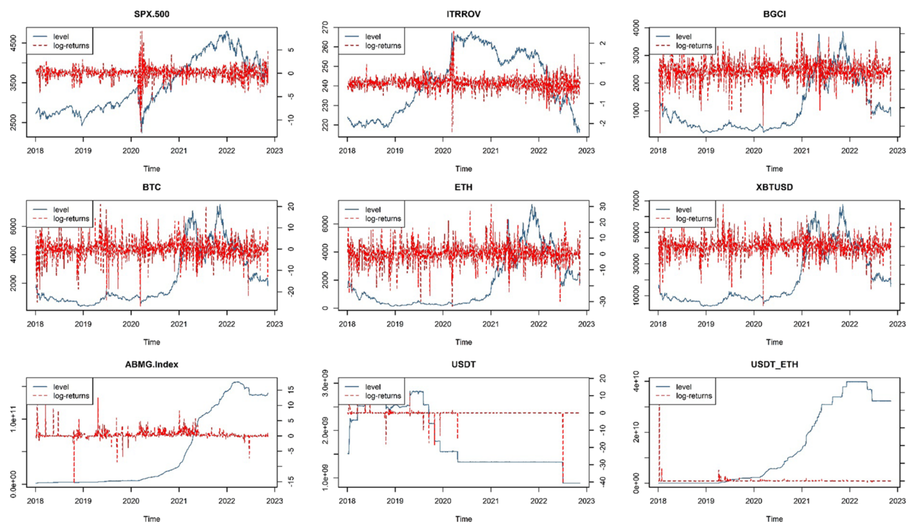

Fig. 3 Time series plots. *Notes*: This figure displays the trajectories of the raw series (blue) and log-returns (red) for the various variables in the sample, which comprises stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH). The sample spans between January 05, 2018, and November 10, 2022

analyzed markets. It is important to mention that over the sample period, we recount several historical trends in digital and conventional financial markets. For instance, the COVID-19 pandemic and geopolitical conflict between Russia and Ukraine are notable event periods common to both market types. Similarly, the sample period covers several trends in cryptocurrency markets, including diverse occasions of the record-low volatility of Bitcoin vis-à-vis stock markets such as Nasdaq and S&P 500; see the respective dynamics in 2020 and 2022,[2] as portrayed in Fig. 2.

Based on (1) a visual analysis of the S&P 500 index and that of Bitcoin[3] and (2) the trajectories shown in Fig. 2,[4] we deduce several downtrends in the market, primarily occurring along the following timeframes. The first covers the period from October 3, 2018, to December 21, 2018; the second is between July 29, 2019, and October 08, 2019; the third falls between February 20, 2020, and March 23, 2020; the fourth ranges from September 02, 2020, to September 30, 2021; the fifth covers the period from January 04, 2022, to March 14, 2022; the sixth falls within the period from April 04, 2022, to June 16, 2022; and the final, based on the analyzed sample, spans the period from August 16, 2022, to September 30, 2022. The final subsample covers the recent period in which Bitcoin is, by number, less volatile than the NASDAQ Composite index and the S&P 500 index, as already discussed. A comparison of the S&P 500 index to the Bitcoin price within these intervals clearly demonstrates, at least visually, that when stocks experience prolonged declines, Bitcoin does not provide a hedge but amplifies the downside risk. We subject this to empirical analysis in this study, considering the role of stablecoin issuances.

[2] https://coinmarketcap.com/headlines/news/by-the-numbers-bitcoin-volatility-nasdaq-sp500/. Assessed on 19–01-2023.

[3] Visit https://klementoninvesting.substack.com/p/another-tail-wagging-the-dog to appreciate the visual inspection of the S&P 500 and Bitcoin prices.

[4] Source: US-IND News, https://usindnews.com/bitcoin-nasdaq-compositeand-sp-500-index-30-day-volatilitybitcoin-nasdaq-composite/. Retrieved on: 11–11-2022.

Table 1 Descriptive statistics, stationarity tests, and correlation matrix

	SPX.500	ITRROV	BGCI	BTC	ETH	XBTUSD	ABMG. Index	USDT	USDT_ETH
Panel A: Descriptive statistics									
Mean	0.0003	0.0000	− 0.0006	0.0002	0.0003	0.0002	0.0040***	− 0.0005	0.0112**
Variance	0.000***	0.000***	0.003***	0.002***	0.004***	0.002***	0.000***	0.000***	0.029***
Skewness	− 0.987***	− 0.096	− 0.686***	− 0.438***	− 0.266***	− 0.534***	2.219***	− 10.175***	31.139***
Ex. Kurtosis	13.137***	7.854***	4.288***	4.290***	4.051***	4.694***	51.098***	217.011***	1010.703***
Jarque Bera	8264.956***	2890.709***	949.265***	897.997***	781.930***	1085.348***	123,203.240***	2,224,961.489***	48,022,812.637***
ERS	− 9.618***	− 11.136***	− 14.272***	− 2.755***	− 13.801***	− 2.750***	− 9.595***	− 14.047***	− 18.398***
Q(20)	122.366***	29.300***	13.950	17.426**	14.009	18.845**	132.233***	3.430	7.552
Q^2(20)	1473.588***	690.103***	20.571**	68.002***	24.050***	43.193***	5.892	0.129	0.116

Pearson	SPX.500	ITRROV	BGCI	BTC	ETH	XBTUSD	ABMG. Index	USDT	USDT_ETH
Panel B: Unconditional pairwise correlations									
SPX.500	1.000***	− 0.245***	0.286***	0.260***	0.301***	0.274***	0.044	0.028	− 0.005
ITRROV		1.000***	− 0.052	− 0.038	− 0.055	− 0.028	− 0.015	− 0.040	− 0.003
BGCI			1.000***	0.907***	0.944***	0.884***	0.000	− 0.084***	0.016
BTC				1.000***	0.801***	0.974***	0.016	− 0.054	0.008
ETH					1.000***	0.780***	0.020	− 0.080***	0.012
XBTUSD						1.000***	0.028	− 0.044	0.009
ABMG. Index							1.000***	0.544***	0.093***
USDT								1.000***	0.009
USDT_ETH									1.000***

This table displays the sample statistics, stationarity test outcomes, and unconditional pairwise correlations between the returns for the various variables in our sample, comprising stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH), spanning between January 05, 2018, and November 10, 2022. ** $p < 0.01$, *** $p < 0.001$

To illustrate the behavior of the various variables in our sample, we present plots of prices and returns simultaneously for clarity in Fig. 3 (see Fig. 8 in the "Appendix"). From these trajectories, we note a consistent behavior of the cryptos (BTC, BGCI, ETH, and XBTUSD).

The uptrends in crypto prices (red lines in Fig. 3 or Panel A of Fig. 8) during late (early) 2021 (2022) are somewhat similar to those shown by the SPX500. In turn, stablecoin issuances (particularly the ABMG index and USD_ETH), which exhibiting some stability across certain periods, also exhibit a similar rising trend in 2021/2022. The exception to this feature is the USDT, which shows a relatively steady trend in capitalization from the first quarter of 2020 through mid-2022, when it records a steep drop. In contrast, the US Treasury (ITRROV) exhibits an interesting trend, whereby a sharp rise was recorded in early 2020 with subsequent up/down trends until the last quarter of 2022, when a huge decline was observed. These are interesting dynamics across conventional and digital financial markets that are worth envisaging through empirical analyses to substantiate or otherwise disprove any suspected cross-market connections while studying the hedging abilities of cryptos during a period of multiple intense stress events.

The log-return trajectories (blue lines in Fig. 3 or Panel B of Fig. 8) for stocks, the US Treasury, and cryptocurrencies exhibit several volatility clusters, whereas fewer such clusters are noticeable for stablecoins.

Table 1 presents the statistical properties that describe the sample; that is, the descriptive statistics, as well as the stationarity and normality characteristics of the data distribution in Panel A, along with the unconditional pairwise correlations between the variables in Panel B.

Over the sample period, in Panel A of Table 1, the mean returns for the sampled stock markets are positive for the analyzed stocks; that is, the SPX500. For the US Treasury, the ITRROV index records negative returns, on average. Among the cryptos, BGCI has negative mean returns, whereas BTC, ETH, and XBTUSD have positive mean returns. Concerning stablecoins, the ABMG index and USDT_ETH record positive dynamics of issuances, while USDT records a negative one. Here, the negative USDT performance could be attributed to the increase in the 2-year, 5-year, and 10-year treasury yields.[5] We record leptokurtic and non-normal distributions for all variables. Meanwhile, all return series are stationary, according to the Elliott, Rothenberg, and Stock (ERS) Unit Root statistics. Backing the visualization of volatility clusters among the SPX500, ITRROV, and all cryptos are statistics from the Ljung-Box test (Q(20) and $Q^2(20)$).

The outcomes of the pairwise correlations (Panel B of Table 1) show several significant associations between diverse assets and conventional and digital financial markets. A (an) significant (insignificant) negative correlation between the SPX500 (cryptos: BTC, ETH, and XBTUSD) and ITRROV is noticeable. USDT also shares significant (insignificant) negative correlations with BGCI and ETH (BTC). While SPX500 is insignificantly and positively correlated with ABMG and USDT, it is negatively correlated with USD_ETH. Meanwhile, ITRROV shares insignificant correlations with all stablecoins. The unconditional correlations present interesting dynamics for envisaging connectedness among system variables in an empirical model.

Econometric framework: the TVP-VAR model

Antonakakis et al.'s (2020) TVP-VAR model offers an extension of the connectedness approach of Diebold and Yilmaz (2014) by allowing the variance–covariance matrix to vary via a Kalman filter estimation with forgetting factors consistent with Koop and Korobilis (2014).

The formularization of the $TVP-VAR(p)$ model is given as:

$$y_t = B_t z_{t-1} + \varepsilon_t \quad \varepsilon_t|\Omega_{t-1} \sim N(0, \Sigma_t) \tag{1}$$

$$vec(B_t) = vec(B_{t-1}) + \xi_t \quad \xi_t|\Omega_{t-1} \sim N(0, \Xi_t) \tag{2}$$

with

$$z_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{pmatrix} \quad B_{t'} = \begin{pmatrix} B_{1t} \\ B_{2t} \\ \vdots \\ B_{pt} \end{pmatrix}$$

[5] Trajectories in the 2-year, 5-year, and 10-year Treasury yields over the sample period are available upon request.

where Ω_{t-1} expresses all available information until $t-1$, y_t and z_t corresponds to $m \times 1$ and $mp \times 1$ vectors, respectively. B_t and B_{it} are $m \times mp$ and $mp \times 1$ dimensional matrices, respectively. ε_t is an $m \times 1$ vector, and ξ_t is $m^2p \times 1$ dimensional vector, with Σ_t, and Ξ_t being $m \times m$ and $m^2p \times m^2p$ dimensional matrices, respectively. $vec(B_t)$ is the vectorization of B_t and is an $m^2p \times 1$ dimensional vector.

Using the Wold representation theorem, we transform the vector moving average (VMA) of TVP-VAR. Consequently, generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) are deduced. Following this, the retrieval of the VMA representation y_t takes its depicted form as $\sum_{j=0}^{\infty} A_{jt}\mu_{t-j}$, where A_{jt} is $m \times m$ dimensional matrix.

The $GIRF\left(\Psi_{ij,t}(H)\right)$ represents the responses of all variables j, following a shock in i computed with an $H-step$ ahead forecast. In our estimations, H is set to 10 steps along a 200-day rolling window (RW). For sensitivity analysis, 200-day and 150-day RW lengths are used along with 20 and 5 steps, respectively, as forecast horizons. $GIRF\left(\Psi_{ij,t}(H)\right)$ is expressed as:

$$GIRF\left(H,\sigma_{j,t},\Omega_{t-1}\right) = E\left(y_{t+H}\middle|e_j = \sigma_{j,t},\Omega_{t-1}\right) - E\left(y_{t+j}\middle|\Omega_{t-1}\right), \tag{3}$$

$$\Psi_{j,t}(H) = \frac{A_{H,t}\Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}}\frac{\sigma_{j,t}}{\sqrt{\Sigma_{jj,t}}}\sigma_{j,t} = \sqrt{\Sigma_{jj,t}}, \tag{4}$$

$$\Psi_{j,t}(H) = \Sigma_{jj,t}^{-\frac{1}{2}} A_{H,t}\Sigma_t e_j, \tag{5}$$

where e_j is an $m \times 1$ selection vector that takes the value of 1 with the selection of jth element, and 0 otherwise. Thence, $GFEVD\left(\widetilde{\Phi}_{ij,t}(H)\right)$ is computed based on $\widetilde{\Phi}_{ij,t}(H)$, which has the following representation:

$$\widetilde{\Phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1}\Psi_{ij,t}^2}{\sum_{j=1}^{m}\sum_{t=1}^{H-1}\Psi_{ij,t}^2}, \tag{6}$$

with $\sum_{j=1}^{m}\widetilde{\Phi}_{ij,t}(H) = 1$, and $\sum_{i,j=1}^{m}\widetilde{\Phi}_{ij,t}(H) = m$.

Hinging on the above data, the total connectedness index (TCI) is:

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^{m}\widetilde{\Phi}_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\Phi}_{ij,t}(H)}{m} * 100. \tag{7}$$

The total directional connectedness (TDC) to others, that is, i transmits its shock to all other variables j is:

$$C_{i\to j,t}(H) = \frac{\sum_{j=1,i\neq j}^{m}\widetilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{m}\widetilde{\Phi}_{ji,t}(H)} * 100. \tag{8}$$

The TDC from others, that is, i receives a shock from all other variables j is expressed as

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1, i\neq j}^{m} \widetilde{\Phi}_{ij,t}(H)}{\sum_{j=1}^{m} \widetilde{\Phi}_{ij,t}(H)} * 100. \tag{9}$$

Net total directional connectedness is defined as:

$$C_{i,t}(H) = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H). \tag{10}$$

Empirical results

The main results based on the TVP-VAR connectedness metric are presented and discussed in this section. To deepen our understanding of the connectedness between conventional and digital financial markets, we report the average (static) connectedness, which measures, on average, the overall connection between system variables, and the dynamic (time-varying) connectedness, which shows the evolution of connectedness among variables across time. Throughout our analysis, the intended system consists of stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH).

To confirm our findings, we substantiate, where necessary, the results from the TVP-VAR with those from the quantile VAR (QVAR) connectedness model[6] of Ando et al. (2022). The QVAR approach is a buildup of Diebold and Yilmaz's (2012) classical connectedness metric under Koenker and Bassett's (1978) quantile regression paradigm. Our sample and context portray several market downward trends; hence, the use of the QVAR approach helps us fit VAR models across the upper (bear) and lower (bull) percentiles. Therefore, using the QVAR methodology, we uncover the network connections accompanying extremely large positive and negative shocks (Bouri et al. 2021; Ghosh et al. 2023; Umar and Bossman 2023).

In all our analyses in this section, the results are based on estimations from a 200-day rolling window, one lag order, and a 10-day forecast horizon. The results for different rolling window lengths and forecast horizons are summarized in the sensitivity analysis.

Averaged connectedness matrix analysis

As per convention, we present the mean connectedness among the system variables over the sample period. The average overall TVP-VAR-based connectedness is presented in the spillover connectedness matrix in Table 2.

From Table 2, we find that the total connectedness index (TCI), which expresses the degree of connectedness between the system variables, is 53.70%. This demonstrates a high level of linkage between the analyzed conventional and digital markets (assets). The TCI suggests that, on average, more than half of the changes in the returns of any of the assets in the system result from connectedness among the system variables. This high level of co-movement between conventional and digital financial markets is comprehensible because stablecoins are pegged against traditional safe assets; therefore, changes in stablecoin issuances are accompanied by changes in traditional

[6] Please, see the work of Ando et al. (2019) for an extended representation of the QVAR steps. Note that, we can use the previously described Eqs. (7) and (10), per Antonakakis et al. (2020), to ascertain the overall and net spillovers in a quantile setting after fitting the VAR across the quantiles of interest.

Table 2 Spillover connectedness matrix using TVP-VAR

	SPX.500	ITRROV	BGCI	BTC	ETH	XBTUSD	ABMG	USDT	USDT_ETH	FROM
SPX.500	60.74	8.16	6.09	5.64	6.26	5.72	2.42	2.89	2.09	39.26
ITRROV	8.82	74.80	2.16	2.49	2.23	2.44	2.68	2.00	2.38	25.20
BGCI	3.42	0.86	26.17	21.83	23.45	21.03	1.63	0.85	0.77	73.83
BTC	3.14	0.98	22.22	26.91	17.28	25.93	1.60	0.94	1.01	73.09
ETH	3.78	1.11	25.91	18.63	29.16	17.84	1.78	0.87	0.91	70.84
XBTUSD	3.25	0.98	21.76	26.36	16.84	27.40	1.48	1.00	0.94	72.60
ABMG	2.32	1.94	2.14	2.00	2.40	1.81	56.00	17.40	14.00	44.00
USDT	2.35	1.81	1.55	1.71	1.75	1.83	21.41	55.19	12.40	44.81
USDT_ETH	2.19	3.22	1.15	2.01	3.89	1.84	13.60	11.78	60.32	39.68
TO	29.27	19.05	82.96	80.68	74.09	78.46	46.59	37.73	34.49	483.32
Inc. Own	90.01	93.85	109.13	107.58	103.26	105.86	102.59	92.92	94.82	cTCI/TCI
NET	− 9.99	− 6.15	9.13	7.58	3.26	5.86	2.59	− 7.08	− 5.18	60.41/53.70

This table displays the spillover connectedness matrix between the various variables in our sample, comprising stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH), spanning between January 05, 2018, and November 10, 2022. This represents the connectedness using a 200-day rolling window, one lag order, and a 10-day forecast horizon

assets, particularly in the yields of US treasuries and commercial papers (Kim 2022). Given the link between these traditional assets and stock markets, it confirms that a price decay in conventional markets is likely to be triggered by stablecoin issuances, which, in parallel, would trigger a switch from traditional digital assets to "stable" assets (coins), the latter phenomenon being entirely within the digital realm. That is, the phenomenon of switching from highly volatile cryptos to stable cryptos is athe previously discussed phenomenon of flight-to-cryptosafety.

We turn to directional spillovers, whereby we analyze the transmission of spillovers from a named asset (market) to all others in the system, as well as the spillovers received by a named asset (market) from all others in the system. We locate the TO (FROM) spillovers across the penultimate (last) row (column) of the connectedness matrix in Table 2. Regarding TO spillovers, we find that the BGCI (82.96%), BTC (80.68%), XBTUSD (78.46%), and ETH (74.09%) cryptocurrencies transmit the largest proportion of spillovers to the system. In terms of FROM spillovers, the largest proportion of system spillovers is received by BGCI. This is understandable because BGCI is a collection of several cryptos. To learn about the net positions of various assets (markets) in the system, we analyze NET spillovers, which can be found in the last row of the spillover connectedness matrix. The results show that stocks (SPX500) and the US Treasury (ITRROV) are net recipients of shocks from the system. All stablecoins are net recipients of system spillovers, except ABMG, which transmits (the lowest) net spillovers. All cryptos are net transmitters of shocks. These results are consistent with the QVAR model across the median (0.05) quantile (see Panel A of Table 4 in the "Appendix"), where all cryptos (and ABMG) are net transmitters, with stocks, the US Treasury, and the two stablecoins being net recipients.

These results are representative of a mean-based model for a sample covering several market downturns. Hence, it is informative to explore connectedness across extreme quantiles of shocks. Since market downturns are representative of lower quantiles, we do this by presenting the quantile connectedness based on the QVAR

Table 3 Spillover connectedness matrix across lower tails (quantiles) using quantile VAR

	SPX.500	ITRROV	BGCI	BTC	ETH	XBTUSD	ABMG	USDT	USDT_ETH	FROM
Panel A: Quantile VAR connectedness at tau 0.05										
SPX.500	19.55	11.35	12.02	12.45	12.12	13.01	9.12	6.62	3.76	80.45
ITRROV	13.34	20.02	11.69	12.15	11.61	12.15	9.09	6.42	3.52	79.98
BGCI	12.76	10.28	15.44	14.95	15.06	14.90	7.73	5.76	3.12	84.56
BTC	12.62	10.67	14.53	16.11	13.99	15.67	7.82	5.67	2.92	83.89
ETH	12.34	10.19	15.49	14.64	16.40	14.94	7.50	5.64	2.87	83.60
XBTUSD	12.54	10.32	14.06	15.28	13.72	16.32	8.13	6.25	3.37	83.68
ABMG	11.77	9.89	9.85	9.96	9.91	10.00	22.26	9.51	6.86	77.74
USDT	9.48	8.17	7.46	7.78	7.48	7.94	12.70	34.05	4.94	65.95
USDT_ETH	5.43	4.80	5.23	5.50	5.62	5.75	13.34	3.71	50.62	49.38
TO	90.28	75.68	90.33	92.70	89.52	94.36	75.44	49.58	31.36	689.24
Inc. Own	109.83	95.70	105.77	108.81	105.92	110.69	97.69	83.62	81.98	cTCI/TCI
NET	9.83	−4.30	5.77	8.81	5.92	10.69	−2.31	−16.38	−18.02	86.15/76.58
Panel B: Quantile VAR connectedness at tau 0.10										
SPX.500	27.71	7.78	12.53	12.15	13.10	12.44	6.41	4.68	3.21	72.29
ITRROV	9.30	33.49	10.82	10.87	10.87	10.94	6.27	4.68	2.76	66.51
BGCI	9.36	6.55	19.42	17.83	18.77	17.65	4.48	3.68	2.26	80.58
BTC	9.31	6.51	17.81	19.87	16.56	19.45	4.41	3.82	2.27	80.13
ETH	9.70	6.63	19.11	16.93	20.57	16.81	4.45	3.58	2.22	79.43
XBTUSD	9.23	6.48	17.64	19.54	16.56	20.26	4.40	3.73	2.16	79.74
ABMG	6.37	6.03	6.99	6.82	7.19	6.87	36.95	13.27	9.52	63.05
USDT	5.21	4.23	4.53	4.72	4.71	4.83	16.19	53.43	2.14	46.57
USDT_ETH	3.43	3.21	4.12	4.09	4.25	4.18	14.63	1.92	60.18	39.82
TO	61.91	47.41	93.56	92.95	92.00	93.16	61.25	39.37	26.53	608.13
Inc. Own	89.61	80.90	112.98	112.81	112.57	113.42	98.19	92.81	86.71	cTCI/TCI
NET	−10.39	−19.10	12.98	12.81	12.57	13.42	−1.81	−7.19	−13.29	76.02/67.57

Table 3 (continued)

	SPX.500	ITRROV	BGCI	BTC	ETH	XBTUSD	ABMG	USDT	USDT_ETH	FROM
Panel C: Quantile VAR connectedness at tau 0.20										
SPX.500	49.69	2.74	9.90	8.85	10.13	8.92	3.99	3.74	2.04	50.31
ITRROV	4.61	61.75	6.00	5.62	6.13	5.60	4.47	3.77	2.04	38.25
BGCI	5.82	2.36	23.77	20.45	21.97	19.91	2.44	2.02	1.25	76.23
BTC	5.39	2.28	20.97	24.50	18.07	23.38	2.27	1.94	1.21	75.50
ETH	6.09	2.66	23.22	18.63	25.24	18.04	2.71	2.01	1.39	74.76
XBTUSD	5.53	2.17	20.60	23.69	17.68	24.93	2.20	2.03	1.18	75.07
ABMG	3.07	3.18	4.28	3.92	4.61	3.83	49.71	15.31	12.09	50.29
USDT	3.52	2.78	2.91	3.08	3.04	3.09	16.80	63.56	1.22	36.44
USDT_ETH	1.59	1.70	2.70	2.64	2.87	2.61	15.67	1.25	68.96	31.04
TO	35.62	19.88	90.58	86.87	84.49	85.39	50.56	32.08	22.41	507.89
Inc. Own	85.31	81.64	114.35	111.37	109.73	110.32	100.27	95.64	91.38	cTCI/TCI
NET	−14.69	−18.36	14.35	11.37	9.73	10.32	0.27	−4.36	−8.62	63.49/56.43
Panel D: Quantile VAR connectedness at tau 0.30										
SPX.500	62.69	2.62	7.30	6.73	7.52	6.71	2.45	2.89	1.09	37.31
ITRROV	4.76	80.10	2.08	2.22	2.41	2.14	2.55	2.58	1.16	19.90
BGCI	3.85	0.67	26.03	21.60	23.68	20.82	1.33	1.28	0.74	73.97
BTC	3.58	0.67	22.14	26.85	18.30	25.51	1.06	1.10	0.79	73.15
ETH	3.99	0.89	25.41	19.21	28.12	18.37	1.78	1.30	0.94	71.88
XBTUSD	3.66	0.55	21.66	25.98	17.77	27.37	1.07	1.17	0.76	72.63
ABMG	1.56	1.50	2.56	2.11	3.10	2.15	58.13	15.49	13.40	41.87
USDT	2.45	1.62	1.76	1.88	2.02	2.16	16.69	70.59	0.82	29.41
USDT_ETH	0.72	0.79	1.51	1.57	1.74	1.59	16.30	0.95	74.85	25.15
TO	24.57	9.30	84.42	81.30	76.54	79.46	43.22	26.76	19.69	445.27
Inc. Own	87.26	89.40	110.45	108.16	104.65	106.83	101.36	97.35	94.54	cTCI/TCI
NET	−12.74	−10.60	10.45	8.16	4.65	6.83	1.36	−2.65	−5.46	55.66/49.47

This table displays the quantile spillover connectedness matrix between the various variables in our sample, comprising stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH), spanning between January 05, 2018, and November 10, 2022. This represents the quantile connectedness using a 200-day rolling window, one lag order, and a 10-day forecast horizon. Panels A, B, C, and D host the connectedness across the quantiles 0.05, 0.10, 0.20, and 0.30, respectively model across the 0.05 (Panel A), 0.10 (Panel A), 0.20 (Panel A), and 0.30 (Panel A) quantiles in Table 3.

Interestingly, we observe (see Table 3) that the TCI of the analyzed system at quantile 0.30 is 49.47% (Panel D), which increases to 56.43% (Panel C), 67.57% (Panel B), and 76.58% (Panel A) along the 0.20, 0.10, and 0.05 quantiles, respectively. From these results, we demonstrate that the connectedness between variables is amplified at the extremes of shocks,[7] especially in downward market trends. For instance, between February and March 2020, the price of Bitcoin decreased by half in two days.[8] The bursting crypto-market bubbles and Russian-Ukrainian conflict-induced market crisis are notable up/downturn events in the sample. This emphasizes the phenomenon that cross-market connectedness is amplified during crisis periods, which is attributable to the rush among nominally rational, yet practically irrational investors for safe assets (Bossman 2021; Bossman et al. 2022b), confirming the operability of the competitive markets theory (Owusu Junior et al. 2021) and the theory of financial contagion (Forbes and Rigobon 2001, 2002) in this context.

Network connectivity

We proceed by analyzing the network connectivity between the system of stocks, the treasury, cryptos, and stablecoins (see Fig. 4). Here, we report the results based on the TVP-VAR estimations (Panel A) and first compare them to their counterparts from the median quantile (0.50) (Panel B), and then to the extreme quantiles 0.05 (Panel C) and 0.95 (Panel D) for downtrends and uptrends, respectively.

We report several interesting findings regarding the role of individual assets in the spillover transmission mechanism. The TVP-VAR network (Panel A of Fig. 4) shows that cryptocurrencies champion spillover transmission through innovation and shocks. All cryptos transmit innovations to treasuries (ITRROV) and stocks (SPX500). USDT_ETH is the only stablecoin whose issuances receive shocks from ETH (principally) and BTC (partially). While USDT issuances do not transmit any shock to the system, they receive innovations from a group of stablecoins gauged by the ABMG index. The ABMG Index is the only net transmitter of shocks to assets other than theta (USDT). Thus, the index's net transmitter position may not affect its viability in a portfolio containing cryptocurrencies because it does not receive shocks from cryptos. In particular, it is worth noting the net recipient status of the individual stablecoins, namely USDT and USDT_ETH. These results are consistent with those in Table 2 for the TVP-VAR spillover connectedness matrix. The TVP-VAR network connectivity dynamics (see Panel A of Fig. 4) are qualitatively similar to those revealed by the QVAR-median-based connectivity network (see Panel B of Fig. 4). For instance, all cryptos are net transmitters of innovations to the US stock and treasury markets; ITRROV and SPX500 are net recipients of spillovers; and among stablecoins, ABMG is the only net transmitter, with one exception: it pushes innovations to USDT_ETH (instead of USDT) and ITRROV.

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[7] In fact, at the upper (0.95) quantile (see Panel B of Table A1 in the Annex), connectedness index also amplifies.

[8] https://www.cnbc.com/2020/03/13/bitcoin-loses-half-of-its-value-in-two-day-plunge.html, CNBC. Assessed on 20–01-2023.

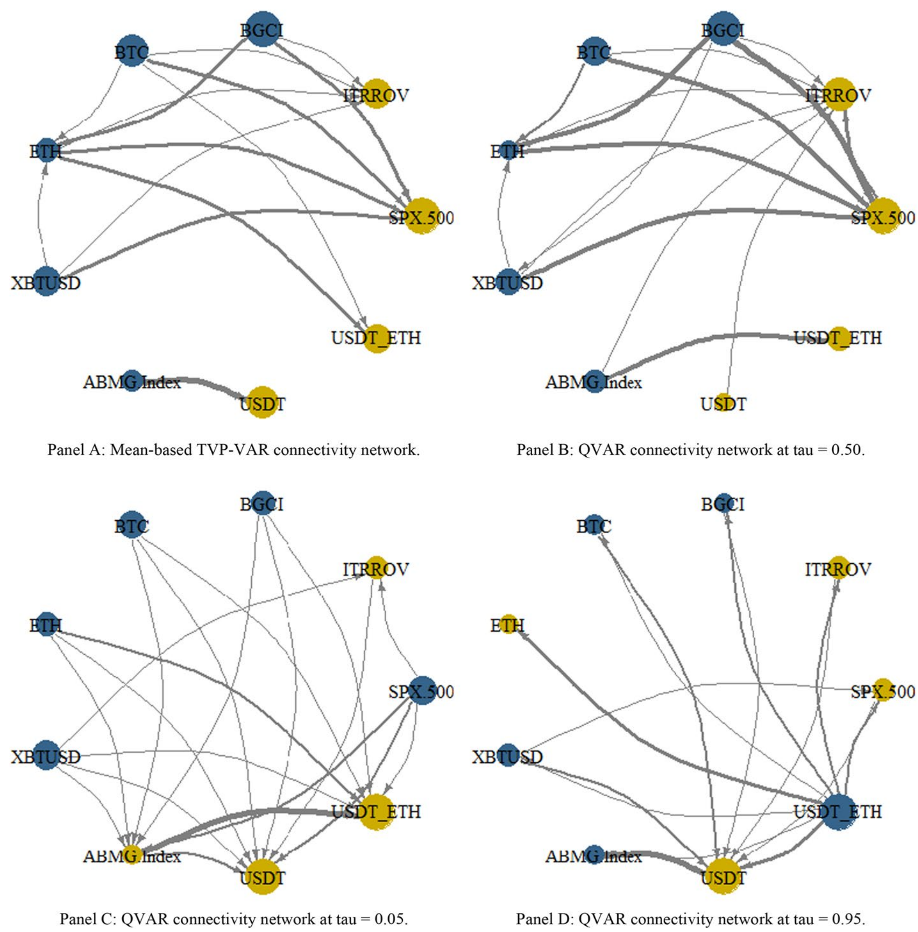


Fig. 4 Network connectedness. *Notes*: This figure presents the averaged network connectedness between the analyzed system, which comprises stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH) based on TVP-VAR estimations using a 200-day rolling window, one lag order, and a 10-day forecast horizon. The sample spans between January 05, 2018, and November 10, 2022. Panel **A** represents the network connectedness under the TVP-VAR model while Panels **B** (tau = 0.50), **C** (tau = 0.05), and **D** (tau = 0.95) represent the network connectedness under the quantile VAR model

The network topology is most complex in the extreme left tail (quantile 0.05; Panel C of Fig. 4). The SPX500 and ABMG switch roles, whereas all other asset roles remain. All cryptos are net transmitters of shocks to the system, and all stablecoins are net recipients of spillovers in downtrend markets, although a basket of stablecoins (ABMG) pushes innovation to individual coins. It is worth noting ITRROV's role as a net recipient, although ITRROV receives innovations only from XBTUSD and not from BGCI, BTC, or ETH. This attribute is appropriate, as investors from conventional markets (SPX500) will fall on treasuries as long as they do not experience a price decay, thereby highlighting the flight-to-safety or flight-to-quality phenomena (Bossman et al. 2022a; Gubareva and Borges 2016; Gubareva and Umar 2023). Meanwhile, during a downward trend, when price decay sets in the treasury market, investors may shift from the conventional market to the digital market for stable digital assets. This is facilitated by the lucrative attributes exhibited by stablecoins via their issuances, thereby confirming the reasoning and theorizing (flight-to-cryptosafety) that stablecoins are the cornerstone for bridging conventional and digital financial markets (Gubareva et al. 2023a). During a market uptrend, on which we place less emphasis, per the extreme right tail (quantile 0.95; Panel D of Fig. 4), ETH switches to the net recipient role among cryptos alongside the SPX500 and ITRROV because of its tendency to make unexpected gains when the financial markets are overperforming. USDT is the only stablecoin that remains a net recipient of system spillovers. Therefore, even at during uptrend, the prominent stablecoin theta can signal investors to take measures against cryptocurrencies that may possess shocks.

Our TVP-VAR and QVAR median-quantile network connectivity findings are qualitatively consistent across the lower tails (0.10, 0.20, and 0.30) of the shock distribution (see Fig. 9 in the "Appendix". Notably, changes in individual (rather than basket) stablecoin issuances are net recipients of spillovers, relative to classical cryptos, which are all net transmitters. Thus, during various extreme lower trends in conventional crypto markets, stablecoins have fewer shocks to transmit through issuances than they receive. This is understandable because vulnerability and fragility are attributes of an emerging market (Li et al. 2023), of which the stablecoin market is no exception. It is worth noting that this reasoning corroborates the observation that in the network topology, cryptos hardly transmit shocks among themselves, but do so intensively across the stock, treasury, and stablecoin markets.

Dynamic connectedness analysis

In this subsection, we analyze the time-varying connectedness among the sampled assets from the digital and conventional financial markets. The TCI varies over time, allowing us to inspect how the overall connectedness between system variables varies

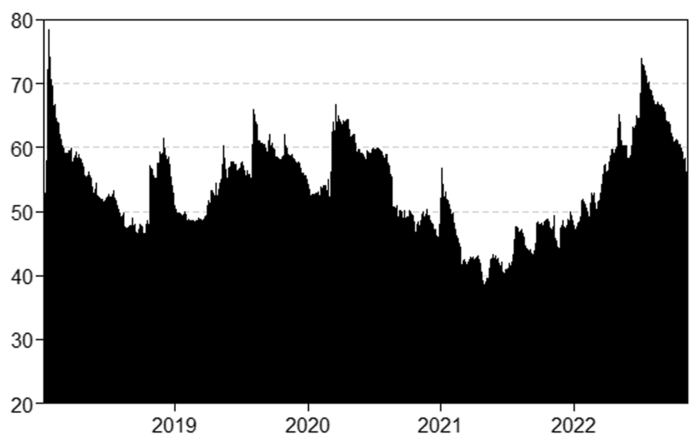


Fig. 5 Total time-varying connectedness. *Notes*: This figure presents the dynamic total (time-varying) connectedness between the analyzed system, which comprises stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH) based on TVP-VAR estimations using a 200-day rolling window, one lag order, and a 10-day forecast horizon. The sample spans between January 05, 2018, and November 10, 2022

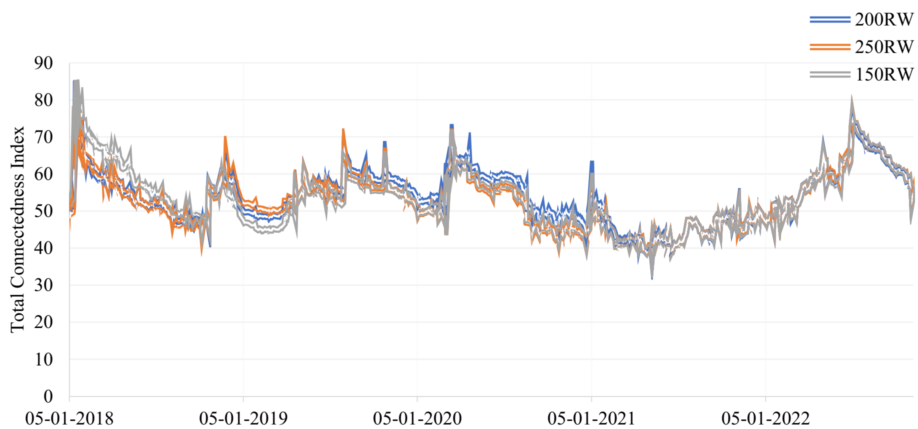


Fig. 6 Total time-varying connectedness across various rolling window lengths. *Notes*: Across the 200-day (blue lines), 250-day (orange lines), and 150-day (grey lines) rolling window lengths, this figure presents the total time-varying connectedness between the analyzed system, which comprises stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH) based on TVP-VAR estimations with a 10-day, 20-day, and 5-day forecast horizons, respectively. The sample spans between January 05, 2018, and November 10, 2022

across various events and stages (trends) in the market. We analyze the total and NET spillovers between the sampled assets (markets).

The TVP-VAR-based total time-varying connectedness among stocks, treasuries, cryptos, and stablecoins is displayed in Fig. 5.

Over the analyzed sample period, Fig. 5 shows that the TCI between stocks, treasuries, cryptos, and stablecoins is high, ranging between 38 and 78%, and responds to uptrends and downtrends in the market, corroborating the periods of up/downtrends we identified during the period. The two most intense TCI hikes occurred in January 2018 (78%) and July 2022 (74%). Our results from the TVP-VAR connectedness using a 200-day rolling window and a 10-day forecast horizon are consistent with those generated when we calibrate the length of the rolling window and forecast horizon. In Fig. 6, we show the time-varying TCI for the 200-day rolling window [200-day RW alongside a 10-day forecast horizon (FH)] in blue lines and compare it to those for a 250-day RW (alongside a 20-day FH), orange lines, and a 150-day RW (alongside a 5-day FH). It is important to note that the results confirm each other with negligible differences in the TCIs along a few data points. All hikes and major trends support each other across the variety of RWs considered and forecasted FH lengths.

The following mechanism explains the generally high connectedness among variables. This mechanism involves the use of safe assets from the traditional financial market to collateralize stablecoins, in accordance with the widely employed design of stable cryptos (Grobys et al. 2021). Therefore, we need to understand that an increase in stablecoin issuances suggests a corresponding increase in the demand, by the issuer, of the underlying safe assets from the conventional financial market. Meanwhile, an excessive peak in demand for traditional safe assets, such as US Treasuries and commercial papers, does not imply a corresponding increase in their respective yields. The reported positive relationship between the issuance of stablecoins and their underlying traditional assets has an inverse effect on the yields associated with these assets (Kim 2022). Hence, investors in conventional (digital, especially crypto) markets are signaled by a possible price decay, forcing them to switch to alternative assets to safeguard their portfolios. The rush and competition for these safe assets drive cross-market connectedness throughout extreme market downturns, although money does not necessarily cross the boundaries between the digital and conventional financial markets. This is true because stablecoins provide an efficient link between conventional and digital markets due to the pegging of the coins against conventional safe assets. Here, the competitive market theory (Owusu Junior et al. 2021), which takes intuition from modern portfolio theory (Markowitz 1952), supports our findings.

Although the total time-varying connectedness demonstrates the evolution of the overall connectedness between the system variables, we cannot observe the sources of spillovers in the transmission mechanism. To achieve this, we analyze NET connectedness, in which each variable's contribution to the system is demonstrated. In the present analysis framework, net spillovers are more important than TO and FROM spillovers. In addition, we generate dynamic NET from TO and FROM time-varying spillovers; hence, our focus on NET rather than TO and FROM spillovers is

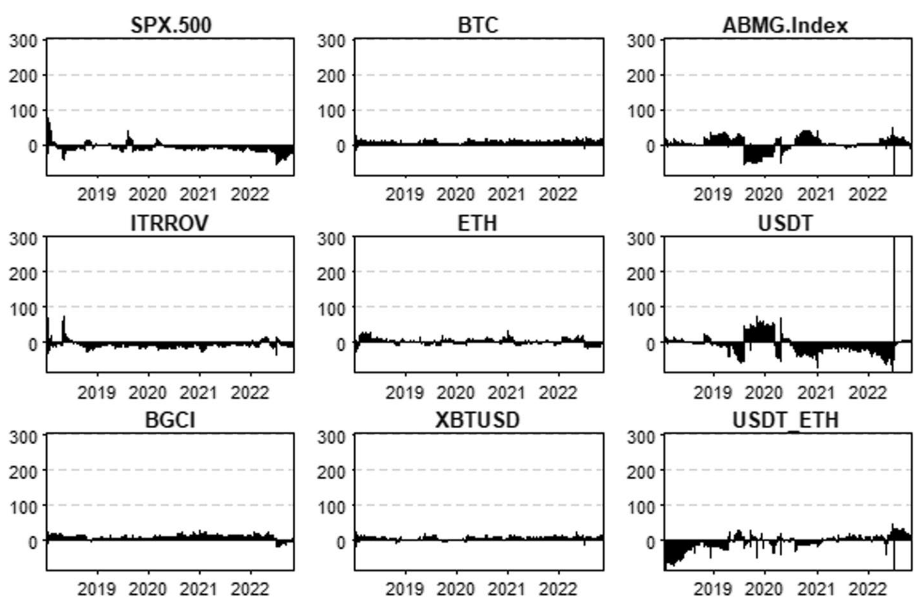


Fig. 7 Net time-varying connectedness. *Notes*: This figure presents the net time-varying connectedness between the analyzed system, which comprises stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH) based on TVP-VAR estimations using a 200-day rolling window, one lag order, and a 10-day forecast horizon. The sample spans between January 05, 2018, and November 10, 2022

reasonable. The time-varying NET spillovers within the analyzed system are shown in Fig. 7.

The time-varying net spillover results demonstrate the following. First, all of the cryptocurrencies are net transmitters of dynamic spillovers across the sample period. However, we also observe ETH's ability to switch roles over time. Second, the SPX500 and ITRROV serve as overall net shock recipients across the sample period. Third, for stablecoins, changes in the issuance of the ABMG index are consistently net transmitters. Although changes in USDT and USDT_ETH issuances show some level of consistency as net recipients of spillovers, they become net transmitters circa 2019/2020, especially for USDT, and for a few months toward the end of the sample period for both (including ABMG). We ascribe this behavior to the most recent crypto crash, observed in 2022. It has become severe since November 2022, alerting investors to the elevated risk of crypto investments.

Consistent with Smales (2019), these findings show that considering cryptocurrencies as safe havens (hedges) is impractical. Furthermore, changes in the issuances of all the analyzed stablecoins are generally net recipients of spillovers. These results confirm that (1) the hedge benefits of cryptos vanish in extreme market trends because they share high connectivity with conventional assets, (2) stablecoins, through issuances, facilitate the switch from traditional digital cryptocurrencies to stablecoins, and (3) because of the pegging of these coins to conventional safe assets, the issuances of stablecoins may provoke the switch from riskier conventional assets, such as stocks, to safer and more stable conventional assets, such as US Treasuries. These phenomena are especially pronounced during crisis periods, when price decay in traditional crypto markets and stocks is common, thus emphasizing flight-to-safety and flight-to-cryptosafety, as previously discussed.

Sensitivity analysis

To confirm our results, we explore the sensitivity of our findings to the lengths of the forecast horizon (FH) and rolling window (RW). Our main analyses have been performed using a 200-day window size alongside a forecast horizon of 10 days. In this subsection, we consider 250-day and 150-day RW lengths accompanied by 20-day and 5-day FH, respectively, and re-estimate the main models in "Averaged connectedness matrix analysis", "Network connectivity" and "Dynamic connectedness analysis" sections.

For "Averaged connectedness matrix analysis" section ("Network connectivity"), Table 5 (Fig. 10) in the "Appendix" presents the re-estimated spillover connectedness matrix (network topologies) within the analyzed system using the TVP-VAR connectedness model across various rolling windows. The results also confirm that all cryptocurrencies are net transmitters, whereas stablecoins, stocks (SPX500), and treasury (ITRROV) are net spillover recipients. Similarly, having found that system connectedness is amplified at market downtrends, Table 6 (see "Appendix") supplements the previously estimated QVAR model after re-estimating the model across the lower (0.05) quantile using a 250-day RW (Panel A) and a 150-day RW (Panel B). The results also show that the TCI is amplified at the lower tails, representing market downtrends. The accompanying network topology (see Fig. 11 in the "Appendix") is also rendered complex across the lower tail, although the conclusions remain.

In "Dynamic connectedness analysis" section, we reestimate the TVP-VAR dynamic connectedness results (see Fig. 12 in the "Appendix"), which confirm the high connectivity driven by stressed market events. The net time-varying transmitter (recipient) roles of cryptos (stocks, treasury, and stablecoins) are also confirmed using the re-estimated models from Fig. 13 in the "Appendix".

The various sets of empirical analyses demonstrate the robustness of our results, substantiating the fact that the study's qualitative conclusions thus far are independent of the lengths of both the rolling window and the forecast horizon.

Concluding remarks

This study provides empirical evidence that supports the economic reasoning underlying the impracticability of the diversification benefits and hedge attributes of cryptocurrencies remaining in force during the downside trends observed in bearish financial markets. The main cornerstone of our investigation is studying the role of stablecoins in spillover transition mechanisms. This study adds to the literature on stablecoins, underscoring the high connectedness between digital and conventional financial markets through the pegging of these coins to conventional safe assets.

We sample multiple assets from conventional and digital financial markets to explore their connectedness amid stablecoins. Our findings reveal that price decays in cryptocurrency markets lead to increases in investments in stablecoins, underscoring the new phenomenon we designate, consistent with Gubareva et al. (2023a), as flight-to-cryptosafety. The analysis demonstrates that stablecoins represent the link that explains the influence of digital markets on conventional financial markets, even if all the money remains within the original markets, not flowing from digital to conventional financial markets, and vice versa.

Overall, our analysis lends empirical evidence to support our argument that no cryptocurrencies should be uncorrelated with stocks during market downturns. Consequently, they are not supposed to diversify, but amplify downside risks. Our outcomes are aligned with previous research that acknowledges that safe haven properties change over time and across markets. We draw insightful conclusions, provoking new thinking regarding portfolio hedge strategies that could potentially benefit investors in searching for less volatile investment performance.

All the same, the risks associated with cryptocurrencies in general, and stablecoins in particular, should not be underestimated and should be carefully assessed in the case of any particular investment. For instance, the profound turmoil in the cryptocurrency market observed during 2022–2023 made regulators deeply worried about what concerns this market. The Financial Stability Board (FSB) recently published its position regarding the international regulation and supervision of crypto trading, highlighting the work already undertaken by the FSB and other international regulatory bodies, focusing on the financial stability risks posed by cryptocurrencies, including stablecoins (FSB 2022). This document states that crypto markets must be subjected to effective regulations commensurate with the risks they pose to investors and financial stability. Notwithstanding the potential benefits of having stablecoins on a balance sheet, such exposures are subject to several risks, such as being a natural hedge for crypto portfolios (Díaz et al. 2023). Recent market situations provide evidence that stablecoins are affected by rare but serious flaws. Their prices are often not as stable as may be inferred from stability-related denominations (Baur and Hoang 2021).

Moreover, stablecoins are more susceptible to reputational and operational risks than are other cryptocurrency assets. The reputational risks that potentially affect stablecoins are linked to a vast number of potential drivers related, for instance, to their proper modus operandi, assuming constant scrutiny of their real backing rates. In addition, the overall reputation of the stablecoin asset class has suffered several allegations of fraud concerning proper stablecoin project design, accusations, and legal charges of misleading and manipulating collateral accountability reports (Díaz et al. 2023). Because of this litigation and generalized worries, stablecoins, as an asset class, have a damaged perception, which has expelled diverse investors. The recently observed collapse of various stablecoin representatives can be primarily attributed to operational risk and unethical and illegal conduct. However, a few of these assets have suffered from speculative behavior, amplifying the risks and volatility of digital instruments. In light of the above, the outcomes of our study are relevant and timely vis-à-vis several challenges faced by investors and regulators of the cryptocurrency market.

Our findings have important implications for market regulations, portfolio management, and future research. Regarding market regulations, the findings highlight the susceptibility of stablecoins to shocks from developed conventional markets and other emerging markets that have been in the system for relatively long periods. Hence, regulators should use extreme changes in these markets as a signal to regulate stablecoin issuances and maintain their stability attributes, thereby ensuring hedge, safe haven, and diversification advantages for investors. Concerning portfolio management, the findings of this study hold merit for large-scale and institutional investors based on the following justification. We find that stablecoin issuances transmit fewer spillovers than they receive, rendering them net recipients across downtrending markets. This indicates that investors who maintain a considerable proportion of emerging digital assets, such as stablecoins, may benefit from the diversification benefits of stablecoins; however, risk-return assessment should be thoroughly performed in each particular case.

Be that as it may, because the emerging digital asset class of stablecoins is highly susceptible to shocks and contagion from traditional cryptos and other conventional financial assets, investors with allocations in stablecoins need to use changes in conventional and digital financial markets as a signal to readjust their portfolios. In terms of future studies, we believe that assessing the frequency-domain spillovers will be important for horizon-based market participants. Additionally, this new phenomenon, designated as the flight-to-cryptosafety, could be tested using other econometric approaches in future studies.

Appendix

See Figs. 8, 9, 10, 11, 12 and 13 and Table 4, 5 and 6.

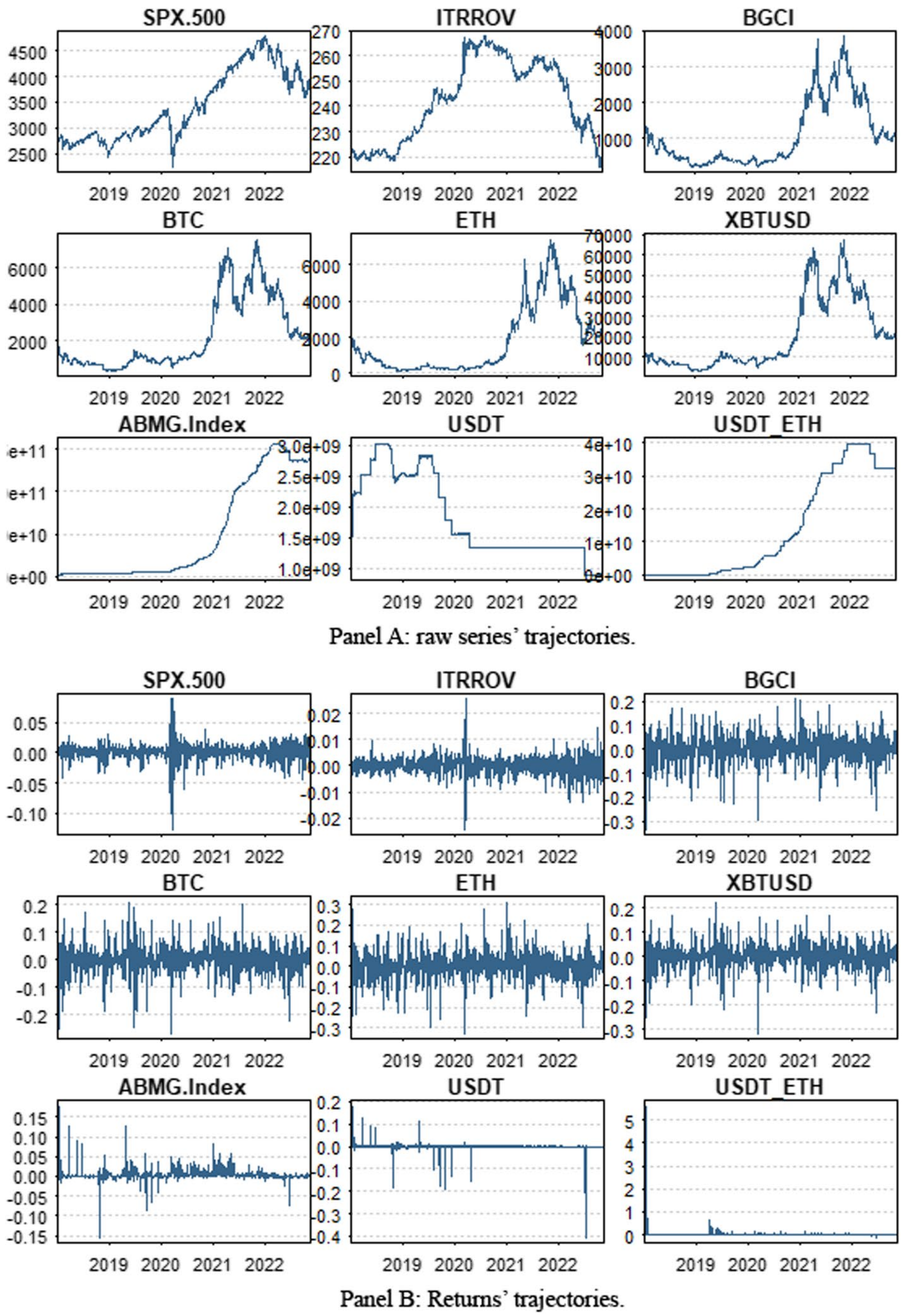


Fig. 8 Individual raw series and log-returns trajectories for the analyzed variables

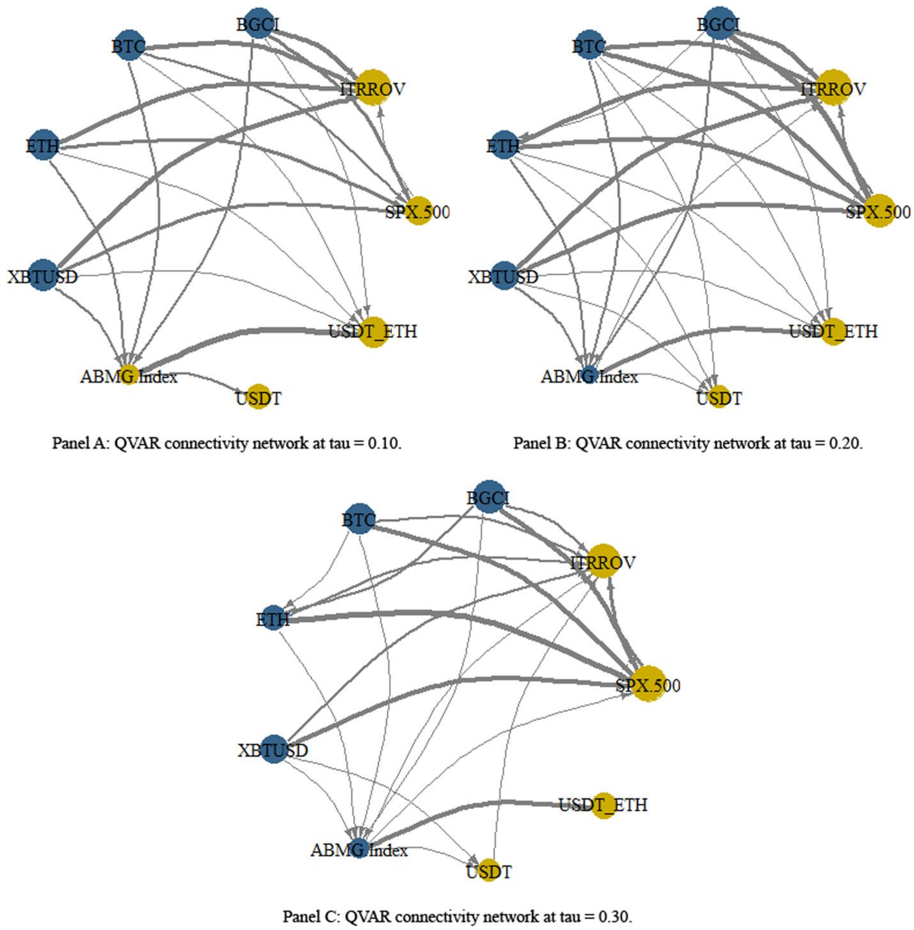


Fig. 9 Network connectedness across lower quantiles. *Notes*: This figure presents the averaged QVAR network connectedness between the analyzed system, which comprises stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH) based on QVAR estimations using a 200-day rolling window, one lag order, and a 10-day forecast horizon. The sample spans between January 05, 2018, and November 10, 2022. Panels **A**, **B**, and **C** represent the quantile network connectedness at 0.10, 0.20, and 0.30 quantiles

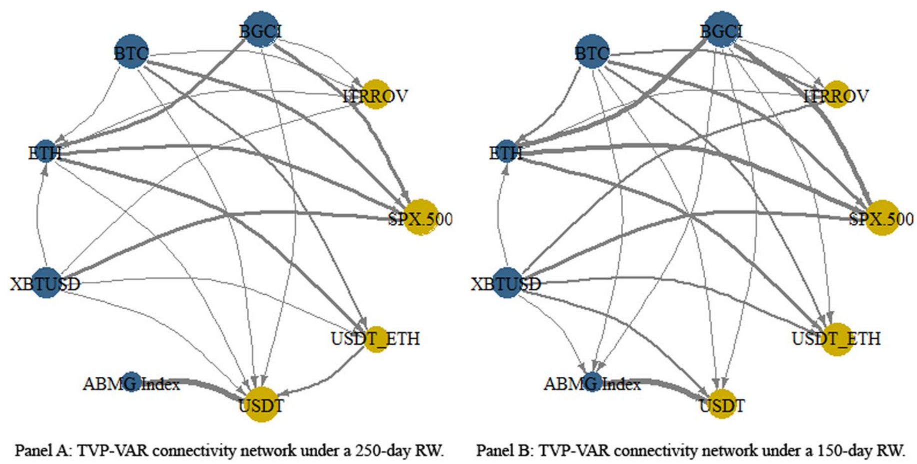


Fig. 10 TVP-VAR network connectedness across various rolling window lengths. *Notes*: This figure presents the averaged network connectedness between the analyzed system, which comprises stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH). Panel **A** is based on TVP-VAR estimations using a 250-day rolling window, one lag order, and a 20-day forecast horizon while Panel **B** is based on TVP-VAR estimations using a 150-day rolling window, one lag order, and a 5-day forecast horizon. The sample spans between January 05, 2018, and November 10, 2022

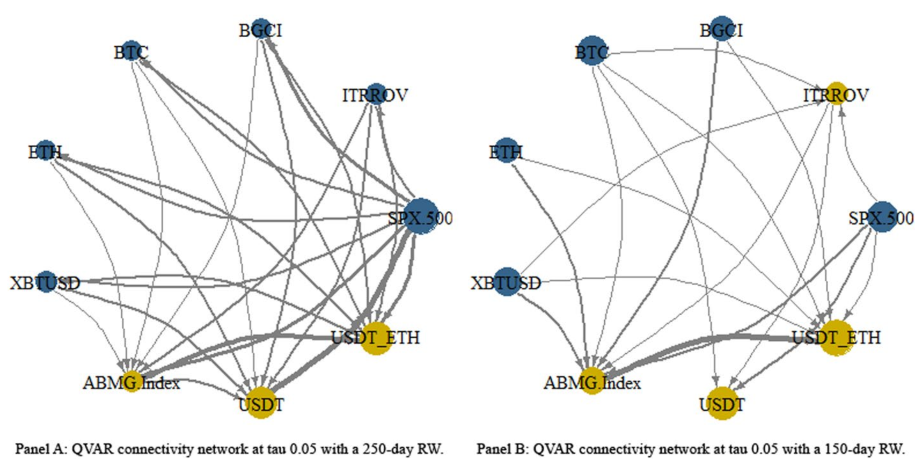
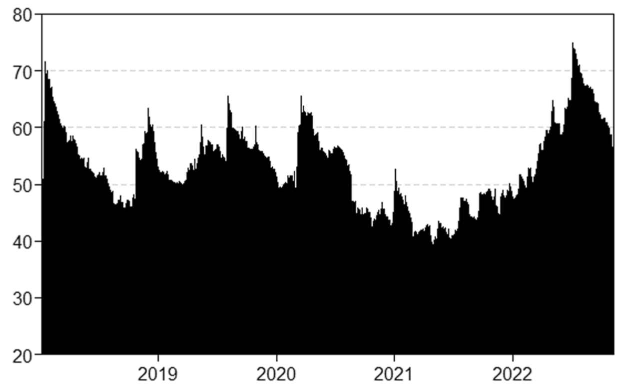
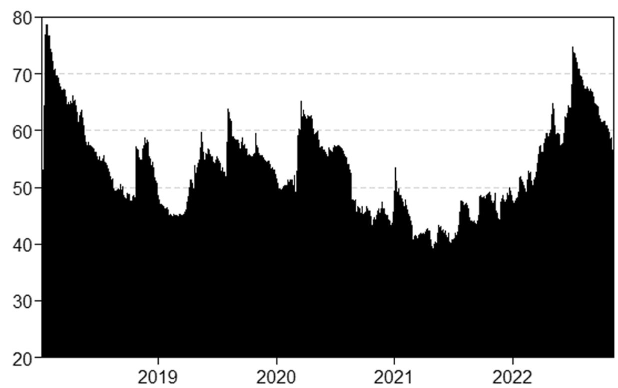


Fig. 11 QVAR left tail network connectedness across various rolling window lengths. *Notes*: This figure presents the averaged QVAR network connectedness between the analyzed system, which comprises stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH). Panel **A** is based on QVAR estimations using a 250-day rolling window, one lag order, and a 20-day forecast horizon while Panel **B** is based on QVAR estimations using a 150-day rolling window, one lag order, and a 5-day forecast horizon. The sample spans between January 05, 2018, and November 10, 2022

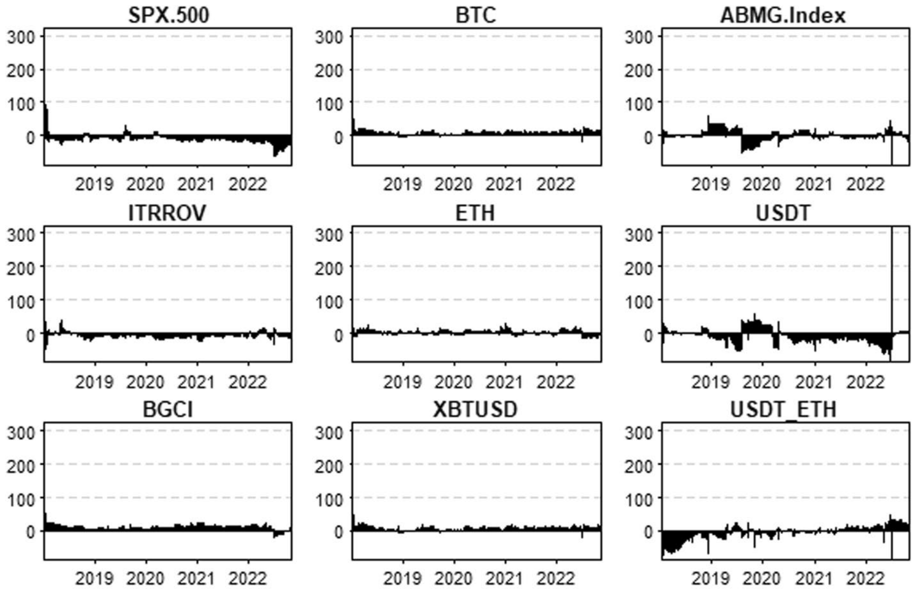


Panel A: Total time-varying connectedness under a 250-day rolling window.

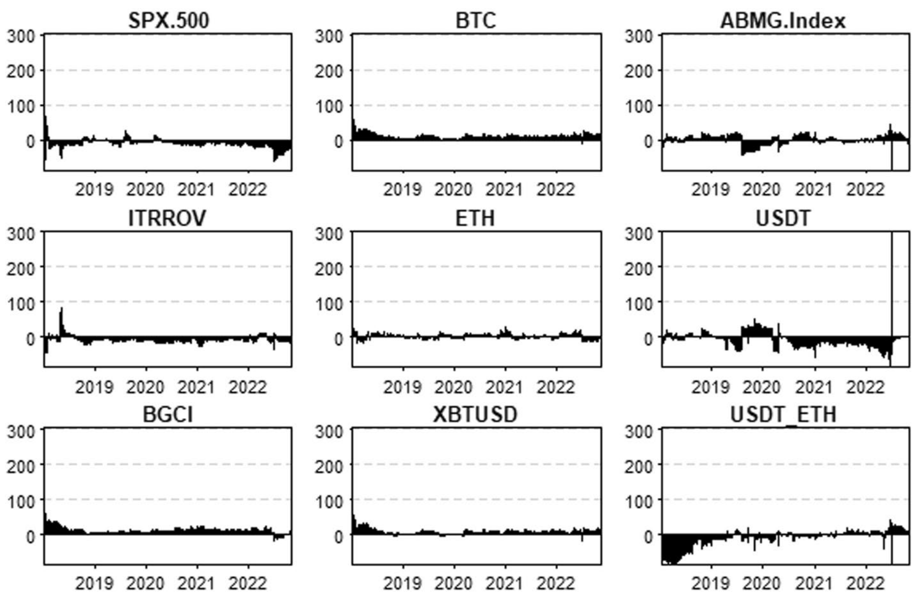


Panel B: Total time-varying connectedness under a 150-day rolling window.

Fig. 12 Total time-varying connectedness under different rolling window lengths. *Notes*: This figure presents the total time-varying connectedness between the analyzed system, which comprises stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH) based on TVP-VAR estimations using one lag order and a 20-day (10-day) forecast horizon for Panel **A** (**B**). Thus, Panel **A** (**B**) shows the total time-varying connectedness under a 250-day (150-day) rolling window specification. The sample spans between January 05, 2018, and November 10, 2022



Panel A: Net time-varying connectedness under a 250-day rolling window.



Panel B: Net time-varying connectedness under a 150-day rolling window.

Fig. 13 Net time-varying connectedness under different rolling window lengths. *Notes*: This figure presents the net time-varying connectedness between the analyzed system, which comprises stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH) based on TVP-VAR estimations using one lag order and a 20-day (10-day) forecast horizon for Panel A (B). Thus, Panel A (B) shows the total time-varying connectedness under a 250-day (150-day) rolling window specification. The sample spans between January 05, 2018, and November 10, 2022

Table 4 Spillover connectedness matrix across the median and upper tails using quantile VAR

	SPX.500	ITRROV	BGCI	BTC	ETH	XBTUSD	ABMG	USDT	USDT_ETH	FROM
Panel A: Quantile VAR connectedness at tau 0.50, i.e., the median quantile										
SPX.500	67.97	6.44	5.68	5.23	5.57	5.52	1.07	1.99	0.53	32.03
ITRROV	8.43	83.46	1.29	1.19	1.24	1.20	1.14	1.36	0.68	16.54
BGCI	2.87	0.36	27.30	22.07	24.57	21.15	0.64	0.66	0.36	72.70
BTC	2.74	0.32	22.62	28.05	18.15	26.70	0.49	0.52	0.40	71.95
ETH	2.94	0.35	26.98	19.40	29.93	18.53	0.71	0.81	0.34	70.07
XBTUSD	2.86	0.23	22.11	27.19	17.71	28.65	0.38	0.51	0.35	71.35
ABMG	0.82	0.29	1.07	0.60	1.36	0.64	65.83	16.40	12.99	34.17
USDT	1.48	0.55	0.75	0.70	0.96	0.98	17.06	76.89	0.63	23.11
USDT_ETH	0.37	0.23	0.54	0.64	0.71	0.64	15.32	0.75	80.80	19.20
TO	22.51	8.78	81.05	77.03	70.27	75.37	36.80	23.01	16.28	411.11
Inc. Own	90.48	92.24	108.35	105.08	100.20	104.02	102.63	99.91	97.09	cTCI/TCI
NET	− 9.52	− 7.76	8.35	5.08	0.20	4.02	2.63	− 0.09	− 2.91	51.39/45.68
Panel B: Quantile VAR connectedness at tau 0.95, i.e., the upper quantile										
SPX.500	16.81	10.00	11.41	11.24	11.26	11.60	10.07	5.49	12.12	83.19
ITRROV	9.63	17.37	10.89	10.94	11.00	11.14	10.62	5.39	13.03	82.63
BGCI	10.42	9.76	13.94	13.38	13.22	13.57	9.38	4.65	11.67	86.06
BTC	10.14	9.86	13.32	14.32	12.54	14.28	9.59	4.69	11.27	85.68
ETH	10.49	10.34	13.23	12.61	13.38	13.00	9.68	5.00	12.26	86.62
XBTUSD	10.03	9.69	13.22	14.13	12.67	14.39	9.84	4.62	11.41	85.61
ABMG	9.81	10.75	10.05	10.11	10.00	10.27	16.21	7.49	15.31	83.79
USDT	7.77	7.50	6.72	7.35	6.26	7.91	13.40	33.51	9.57	66.49
USDT_ETH	8.77	9.63	8.78	9.18	8.44	9.19	13.69	5.24	27.08	72.92
TO	77.07	77.54	87.62	88.93	85.39	90.96	86.28	42.57	96.64	733.00
Inc. Own	93.88	94.91	101.56	103.26	98.76	105.34	102.49	76.09	123.72	cTCI/TCI
NET	− 6.12	− 5.09	1.56	3.26	− 1.24	5.34	2.49	− 23.91	23.72	91.62/81.44

This table displays the quantile spillover connectedness matrix between the various variables in our sample, comprising stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH), spanning between January 05, 2018, and November 10, 2022. This represents the quantile connectedness using a 200-day rolling window, one lag order, and a 10-day forecast horizon. Panel A hosts the connectedness across the median (0.50) quantile while Panel B caters for the upper (0.95) quantile

Table 5 TVP-VAR spillover matrix under different rolling window lengths

	SPX.500	ITRROV	BGCI	BTC	ETH	XBTUSD	ABMG	USDT	USDT_ETH	FROM
Panel A: 250-day rolling window										
SPX.500	61.98	8.19	5.95	5.59	6.20	5.66	2.38	2.37	1.68	38.02
ITRROV	8.91	75.38	2.00	2.42	2.08	2.38	2.59	1.90	2.35	24.62
BGCI	3.17	0.81	26.15	21.87	23.25	21.05	1.79	1.00	0.91	73.85
BTC	2.97	0.98	22.26	26.94	17.18	25.97	1.62	0.94	1.13	73.06
ETH	3.57	0.97	25.87	18.61	29.24	17.81	1.88	0.93	1.13	70.76
XBTUSD	3.06	0.97	21.80	26.41	16.75	27.44	1.50	0.99	1.07	72.56
ABMG	2.26	1.90	2.56	2.34	2.55	2.11	56.93	15.54	13.83	43.07
USDT	2.29	1.77	1.94	1.96	1.88	2.10	19.23	57.96	10.86	42.04
USDT_ETH	1.72	2.92	1.42	2.71	3.42	2.54	13.26	9.32	62.69	37.31
TO	27.94	18.53	83.81	81.90	73.30	79.62	44.25	32.98	32.97	475.29
Inc. Own	89.92	93.91	109.96	108.85	102.54	107.06	101.17	90.94	95.65	cTCI/TCI
NET	− 10.08	− 6.09	9.96	8.85	2.54	7.06	1.17	− 9.06	− 4.35	59.41/52.81
Panel A: 150-day rolling window										
SPX.500	62.04	8.23	6.04	5.54	6.43	5.62	2.23	2.29	1.58	37.96
ITRROV	8.81	75.14	2.07	2.46	2.23	2.41	2.55	1.92	2.40	24.86
BGCI	3.14	0.82	26.07	21.79	23.07	20.96	2.10	1.36	0.69	73.93
BTC	2.88	1.00	22.23	26.81	17.05	25.84	1.92	1.23	1.05	73.19
ETH	3.48	0.97	25.86	18.69	28.57	17.89	2.31	1.46	0.78	71.43
XBTUSD	2.98	0.99	21.79	26.30	16.64	27.31	1.76	1.25	0.98	72.69
ABMG	2.10	1.90	3.24	2.91	2.88	2.62	56.98	14.93	12.44	43.02
USDT	2.23	1.84	2.62	2.56	2.19	2.62	18.26	57.57	10.11	42.43
USDT_ETH	1.74	3.19	1.60	2.98	3.45	2.79	13.00	10.63	60.63	39.37
TO	27.36	18.94	85.45	83.22	73.93	80.75	44.11	35.08	30.03	478.88
Inc. Own	89.40	94.09	111.52	110.03	102.50	108.06	101.09	92.65	90.66	cTCI/TCI
NET	− 10.60	− 5.91	11.52	10.03	2.50	8.06	1.09	− 7.35	− 9.34	59.86/53.21

This table displays the spillover connectedness matrix between the various variables in our sample, comprising stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH), spanning between January 05, 2018, and November 10, 2022. Panel A represents the connectedness using a 150-day rolling window, one lag order, and a 5-day forecast horizon while Panel B shows the connectedness using a 250-day rolling window, one lag order, and a 20-day forecast horizon in a TVP-VAR model

Table 6 Lower (0.05) quantile spillover connectedness under different rolling window lengths

	SPX.500	ITRROV	BGCI	BTC	ETH	XBTUSD	ABMG	USDT	USDT_ETH	FROM
Panel B: Quantile VAR connectedness at tau 0.05 using a 250-day rolling window										
SPX.500	21.2	12.5	11.8	11.7	12.1	12.0	9.0	5.7	4.0	78.8
ITRROV	16.2	19.8	11.6	11.4	11.7	11.8	8.4	5.7	3.5	80.2
BGCI	15.9	11.8	14.2	13.9	14.2	14.3	7.6	5.0	3.1	85.8
BTC	15.6	11.8	13.6	14.6	13.4	15.0	7.9	5.2	2.9	85.4
ETH	15.8	11.9	14.4	13.6	15.0	13.9	7.8	4.8	2.9	85.0
XBTUSD	15.2	11.7	13.7	14.7	13.3	15.2	8.1	5.0	3.2	84.8
ABMG	14.2	11.3	9.9	9.7	10.1	10.0	20.9	7.8	6.2	79.1
USDT	12.4	9.4	7.7	7.8	7.8	8.3	11.6	30.6	4.5	69.4
USDT_ETH	9.3	7.2	6.4	6.4	6.4	6.7	12.4	3.2	42.0	58.0
TO	114.5	87.6	89.0	89.1	89.0	92.0	72.8	42.4	30.2	706.6
Inc. Own	135.7	107.4	103.2	103.7	104.0	107.2	93.7	73.0	72.2	cTCI/TCI
NET	35.7	7.4	3.2	3.7	4.0	7.2	− 6.4	− 27.0	− 27.8	88.32/78.51
Panel A: Quantile VAR connectedness at tau 0.05 using a 150-day rolling window										
SPX.500	20.03	11.08	12.09	12.41	12.26	12.43	8.31	7.31	4.06	79.97
ITRROV	13.42	20.47	11.93	12.57	11.80	12.29	7.51	6.67	3.35	79.53
BGCI	12.79	10.40	15.67	15.19	15.26	14.91	6.56	6.04	3.17	84.33
BTC	12.23	10.14	14.76	16.23	14.35	15.74	6.95	6.35	3.25	83.77
ETH	12.83	10.41	15.51	14.89	16.33	14.64	6.50	5.81	3.07	83.67
XBTUSD	12.84	10.41	14.32	15.95	13.84	16.10	6.84	6.30	3.40	83.90
ABMG	10.92	9.67	9.35	9.38	9.57	9.41	23.28	11.42	6.99	76.72
USDT	10.19	8.68	7.24	8.13	7.35	7.78	12.58	33.17	4.87	66.83
USDT_ETH	5.77	4.81	5.28	5.51	5.50	5.66	13.24	3.61	50.62	49.38
TO	91.00	75.59	90.48	94.05	89.93	92.86	68.50	53.51	32.17	688.10
Inc. Own	111.03	96.06	106.15	110.28	106.26	108.96	91.78	86.68	82.79	cTCI/TCI
NET	11.03	− 3.94	6.15	10.28	6.26	8.96	− 8.22	− 13.32	− 17.21	86.01/76.46

This table displays the lower (0.05) quantile spillover connectedness matrix between the various variables in our sample, comprising stocks (SPX 500), the US Treasury (ITRROV), cryptocurrencies (BGCI, BTC, ETH, and XBTUSD), and stablecoins (ABMG, USDT, and USD_ETH), spanning between January 05, 2018, and November 10, 2022. Panel A presents the results using a 150-day rolling window, one lag order, and a 5-day forecast horizon while Panels B shows the results using a 250-day rolling window, one lag order, and a 20-day forecast horizon in a TVP-VAR model

Abbreviations

ABMG Index	Ahmed Bossman Mariya Gubareva Index
BGCI	Bloomberg Galaxy Crypto Index
BTC	Bitcoin
ETH	Ethereum
FH	Forecast horizon
GFEVD	Generalized forecast error variance decomposition
GIRF	Generalized impulse response function
NASDAQ	National Association of Securities Dealers Automated Quotation
RW	Rolling window
S&P	Standard and poor's
TCI	Total connectedness index
TVP-VAR	Time-varying parameter vector auto-regressions
US	The United States of America
VMA	Vector moving average

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Declarations

Competing interests
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References

Agyei SK, Adam AM, Bossman A, Asiamah O, Owusu Junior P, Asafo-Adjei R, Asafo-Adjei E (2022a) Does volatility in cryptocurrencies drive the interconnectedness between the cryptocurrencies market? Insights from wavelets. Cogent Econ Finance. https://doi.org/10.1080/23322039.2022.2061682

Agyei SK, Owusu Junior P, Bossman A, Asafo-Adjei E, Asiamah O, Adam AM (2022b) Spillovers and contagion between BRIC and G7 markets: new evidence from time-frequency analysis. PLoS ONE 17(7):e0271088. https://doi.org/10.1371/journal.pone.0271088

Agyei SK, Umar Z, Bossman A, Teplova T (2023) Dynamic connectedness between global commodity sectors, news sentiment, and sub-Saharan African equities. Emerg Mark Rev 56:101049. https://doi.org/10.1016/j.ememar.2023.101049

Ali S, Naveed M, Hanif H, Gubareva M (2024) The resilience of shariah-compliant investments: probing the static and dynamic connectedness between gold-backed cryptocurrencies and GCC equity markets. Int Rev Financ Anal 91:103045. https://doi.org/10.1016/j.irfa.2023.103045

Ando T, Greenwood-Nimmo M, Shin Y (2022) Quantile connectedness: modeling tail behavior in the topology of financial networks. Manag Sci 68(4):2401–2431. https://doi.org/10.1287/mnsc.2021.3984

Ante L, Fiedler I, Strehle E (2021) The influence of stablecoin issuances on cryptocurrency markets. Financ Res Lett 41:101867

Antonakakis N, Chatziantoniou I, Gabauer D (2020) Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. J Risk Financ Manag 13(4):84. https://doi.org/10.3390/jrfm13040084

Bahloul S, Mroua M, Naifar N (2021) Are Islamic indexes, Bitcoin and gold, still "safe-haven" assets during the COVID-19 pandemic crisis? Int J Islam Middle East Finance Manag. https://doi.org/10.1108/IMEFM-06-2020-0295

Baruník J, Křehlík T (2018) Measuring the frequency dynamics of financial connectedness and systemic risk. J Financ Econometr 16(2):271–296

Baur DG, Hoang LT (2021) A crypto safe haven against Bitcoin. Financ Res Lett 38:101431. https://doi.org/10.1016/j.frl.2020.101431

Będowska-Sójka B, Kliber A (2022) Can cryptocurrencies hedge oil price fluctuations? A pandemic perspective. Energy Econ 115:106360. https://doi.org/10.1016/j.eneco.2022.106360

Bossman A (2021) Information flow from COVID-19 pandemic to Islamic and conventional equities: an ICEEMDAN-induced transfer entropy analysis. Complexity 2021:1–20. https://doi.org/10.1155/2021/4917051
Bossman A, Agyei SK (2022) Interdependence structure of global commodity classes and African equity markets: a vector wavelet coherence analysis. Resour Policy 79(December):103039. https://doi.org/10.1016/j.resourpol.2022.103039
Bossman A, Agyei SK, Owusu Junior P, Agyei EA, Akorsu PK, Marfo-Yiadom E, Amfo-Antiri G (2022a) Flights-to-and-from-quality with Islamic and conventional bonds in the COVID-19 pandemic era: ICEEMDAN-based transfer entropy. Complexity 2022:1–25. https://doi.org/10.1155/2022/1027495
Bossman A, Owusu Junior P, Tiwari AK (2022b) Dynamic connectedness and spillovers between Islamic and conventional stock markets: time- and frequency-domain approach in COVID-19 era. Heliyon. https://doi.org/10.1016/j.heliyon.2022.e09215
Bossman A, Umar Z, Agyei SK, Teplova T (2023) The impact of the US yield curve on sub-Saharan African equities. Finance Res Lett 1:103636. https://doi.org/10.1016/j.frl.2023.103636
Bouri E, Gupta R, Lau CKM, Roubaud D, Wang S (2018) Bitcoin and global financial stress: a copula-based approach to dependence and causality in the quantiles. Q Rev Econ Finance 69:297–307. https://doi.org/10.1016/j.qref.2018.04.003
Bouri E, Id LK, Azoury N (2022) Bitcoin and S&P500: Co-movements of high-order moments in the time-frequency domain. PLoS ONE 17(11):1–15. https://doi.org/10.1371/journal.pone.0277924
Bouri E, Saeed T, Vo XV, Roubaud D (2021) Quantile connectedness in the cryptocurrency market. J Int Finan Markets Inst Money 71:101302. https://doi.org/10.1016/j.intfin.2021.101302
Bouri E, Shahzad SJH, Roubaud D, Kristoufek L, Lucey B (2020) Bitcoin, gold, and commodities as safe havens for stocks: new insight through wavelet analysis. Q Rev Econ Finance 77:156–164. https://doi.org/10.1016/j.qref.2020.03.004
Briola A, Vidal-Tomás D, Wang Y, Aste T (2023) Anatomy of a stablecoin's failure: the terra-luna case. Financ Res Lett 51:103358. https://doi.org/10.1016/j.frl.2022.103358
Conlon T, McGee R (2020) Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. Finance Res Lett 35(May):101607. https://doi.org/10.1016/j.frl.2020.101607
Corbet S, Lucey B, Peat M, Vigne S (2018) Bitcoin futures—what use are they? Econ Lett 172:23–27. https://doi.org/10.1016/j.econlet.2018.07.031
Díaz A, Esparcia C, Huélamo D (2023) Stablecoins as a tool to mitigate the downside risk of cryptocurrency portfolios. N Am J Econ Finance 64:101838. https://doi.org/10.1016/j.najef.2022.101838
Diebold FX, Liu L, Yilmaz K (2017) Commodity connectedness. In NBER working paper series (No. 23685; Vol. 23685). http://www.nber.org/papers/w23685
Diebold FX, Yilmaz K (2012) Better to give than to receive: predictive directional measurement of volatility spillovers. Int J Forecast 28(1):57–66. https://doi.org/10.1016/J.IJFORECAST.2011.02.006
Diebold FX, Yilmaz K (2014) On the network topology of variance decompositions: measuring the connectedness of financial firms. J Econometr 182(1):119–134. https://doi.org/10.1016/J.JECONOM.2014.04.012
Duan K, Urquhart A (2023) The instability of stablecoins. Finance Res Lett 52:103573. https://doi.org/10.1016/j.frl.2022.103573
Fiedler I, Ante L (2023) Stablecoins. In: Baker HK, Benedetti H, Nikbakht E, Smith SS (eds) The emerald handbook on cryptoassets: investment opportunities and challenges. Emerald Publishing Limited, Leeds, pp 93–105. https://doi.org/10.1108/978-1-80455-320-620221007
Forbes KJ, Rigobon R (2001) Measuring contagion: conceptual and empirical issues. In: International financial contagion. Springer, New York, pp 43–66. https://doi.org/10.1007/978-1-4757-3314-3_3
Forbes KJ, Rigobon R (2002) No contagion, only interdependence: measuring stock market comovements. J Finance 57(5):2223–2261. https://doi.org/10.1111/0022-1082.00494
FSB (2022) FSB statement on international regulation and supervision of crypto-asset activities. Financial Stability Board-FSB. https://www.fsb.org/wp-content/uploads/P110722.pdf
Gadzinski G, Castello A, Mazzorana F (2022) Stablecoins: does design affect stability? Finance Res Lett. https://doi.org/10.1016/j.frl.2022.103611
Ghabri Y, Rhouma OB, Gana M, Guesmi K, Benkraiem R (2022) Information transmission among energy markets, cryptocurrencies, and stablecoins under pandemic conditions. Int Rev Financ Anal 82:102197. https://doi.org/10.1016/j.irfa.2022.102197
Ghosh B, Gubareva M, Zulfiqar N, Bossman A (2023) Is there a nexus between NFT, DeFi and carbon allowances during extreme events? China Finance Rev Int. https://doi.org/10.1108/CFRI-03-2023-0057
Giudici P, Leach T, Pagnottoni P (2022) Libra or Librae? Basket based stablecoins to mitigate foreign exchange volatility spillovers. Finance Res Lett 44:102054. https://doi.org/10.1016/j.frl.2021.102054
Grobys K, Junttila J, Kolari JW, Sapkota N (2021) On the stability of stablecoins. J Empir Finance 64:207–223. https://doi.org/10.1016/j.jempfin.2021.09.002
Gubareva M, Borges R (2016) Typology for flight-to-quality episodes and downside risk measurement. Appl Econ 48(10):835–853. https://doi.org/10.1080/00036846.2015.1088143
Gubareva M, Umar Z (2023) Emerging market debt and the COVID-19 pandemic: a time–frequency analysis of spreads and total returns dynamics. Int J Finance Econ 28(1):112–126. https://doi.org/10.1002/ijfe.2408
Gubareva M, Bossman A, Teplova T (2023a) Stablecoins as the cornerstone in the linkage between the digital and conventional financial markets. N Am J Econ Finance 68:101979. https://doi.org/10.1016/j.najef.2023.101979
Gubareva M, Umar Z, Teplova T, Vo XV (2023b) Flights-to-quality from EM bonds to safe-haven US treasury securities: a time-frequency analysis. Emerg Mark Finance Trade 59(2):338–362. https://doi.org/10.1080/1540496X.2022.2103399
Harvey CR (2014) Bitcoin myths and facts. SSRN Electron J, 1–10. https://ssrn.com/abstract=2479670
Hasan MB, Hassan MK, Karim ZA, Rashid MM (2022) Exploring the hedge and safe haven properties of cryptocurrency in policy uncertainty. Finance Res Lett 46(PA):102272. https://doi.org/10.1016/j.frl.2021.102272
Heliodoro P, Dias R, Alexandre P (2020) Financial contagion between the US and emerging markets: COVID-19 pandemic case. In: Economics & management: how to cope with disrupted times. https://doi.org/10.31410/eman.s.p.2020.119

Jana S, Sahu TN (2023a) Can diversification be improved by using cryptocurrencies? Evidence from Indian equity market. J Financ Econ Policy 15(6):551–573. https://doi.org/10.1108/JFEP-02-2023-0047
Jana S, Sahu TN (2023b) Is the cryptocurrency market a hedge against stock market risk? A Wavelet and GARCH approach. Econ Notes 52(3):e12227. https://doi.org/10.1111/ecno.12227
Jana S, Sahu TN, Pandey KD (2023) Revisiting the cryptocurrencies role in stock markets: ADCC-GARCH and Wavelet Coherence. Macroecon Finance Emerg Mark Econ. https://doi.org/10.1080/17520843.2023.2211380
Kim SR (2022) How the cryptocurrency market is connected to the financial market. SSRN Electron J, 1–45. https://ssrn.com/abstract=4106815
Klement J (2022) Another tail wagging the dog. https://klementoninvesting.substack.com/p/another-tail-wagging-the-dog
Koenker R, Bassett G (1978) Regression quantiles. Econometrica 46(1):33. https://doi.org/10.2307/1913643
Koop G, Korobilis D (2014) A new index of financial conditions. Eur Econ Rev 71:101–116. https://doi.org/10.1016/J.EUROECOREV.2014.07.002
Kristoufek L (2021) Tethered, or untethered? On the interplay between stablecoins and major cryptoassets. Finance Res Lett 43:101991. https://doi.org/10.1016/j.frl.2021.101991
Kumar S, Patel R, Iqbal N, Gubareva M (2023) Interconnectivity among cryptocurrencies, NFTs, and DeFi: evidence from the Russia-Ukraine conflict. N Am J Econ Finance 6:8. https://doi.org/10.1016/j.najef.2023.101983
Kyriazis NA, Papadamou S, Tzeremes P (2023) Are benchmark stock indices, precious metals or cryptocurrencies efficient hedges against crises? Econ Model 128:106502. https://doi.org/10.1016/j.econmod.2023.106502
Li Z, Mo B, Nie H (2023) Time and frequency dynamic connectedness between cryptocurrencies and financial assets in China. Int Rev Econ Finance. https://doi.org/10.1016/j.iref.2023.01.015
Markowitz H (1952) Portfolio selection. J Finance 7(11):77–91
Mensi W, Gubareva M, Ko H-U, Vo XV, Kang SH (2023) Tail spillover effects between cryptocurrencies and uncertainty in the gold, oil, and stock markets. Financ Innov 9:92. https://doi.org/10.1186/s40854-023-00498-y
Mensi W, Gubareva M, Kang S (2024) Frequency connectedness between DeFi and cryptocurrency markets. Q Rev Econ Finance. https://doi.org/10.1016/j.qref.2023.11.001
Nedved M, Kristoufek L (2022) Safe havens for Bitcoin. Finance Res Lett. https://doi.org/10.1016/j.frl.2022.103436
Nguyen TVH, Nguyen TVH, Nguyen TC, Pham TTA, Nguyen QMP (2022) Stablecoins versus traditional cryptocurrencies in response to interbank rates. Financ Res Lett 47:102744. https://doi.org/10.1016/j.frl.2022.102744
Owusu Junior P, Agyei SK, Adam AM, Bossman A (2022) Time-frequency connectedness between food commodities: new implications for portfolio diversification. Environmental Challenges 9(December):100623. https://doi.org/10.1016/j.envc.2022.100623
Owusu Junior P, Frimpong S, Adam AM, Agyei SK, Gyamfi EN, Agyapong D, Tweneboah G (2021) COVID-19 as information transmitter to global equity markets: evidence from CEEMDAN-based transfer entropy approach. Math Probl Eng. https://doi.org/10.1155/2021/8258778
Ren B, Lucey B (2022) A clean, green haven? Examining the relationship between clean energy, clean and dirty cryptocurrencies. Energy Econ 109:105951. https://doi.org/10.1016/j.eneco.2022.105951
Selmi R, Mensi W, Hammoudeh S, Bouoiyour J (2018) Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. Energy Econ 74:787–801. https://doi.org/10.1016/j.eneco.2018.07.007
Shahzad SJH, Bouri E, Roubaud D, Kristoufek L, Lucey B (2019) Is Bitcoin a better safe-haven investment than gold and commodities? Int Rev Financ Anal 63:322–330. https://doi.org/10.1016/J.IRFA.2019.01.002
Sharma U, Karmakar M (2023) Are gold, USD, and Bitcoin hedge or safe haven against stock? The implication for risk management. Rev Financ Econ 41(1):43–64. https://doi.org/10.1002/rfe.1160
Smales LA (2019) Bitcoin as a safe haven: is it even worth considering? Financ Res Lett 30:385–393. https://doi.org/10.1016/j.frl.2018.11.002
Syuhada K, Suprijanto D, Hakim A (2022) Comparing gold's and Bitcoin's safe-haven roles against energy commodities during the COVID-19 outbreak: a vine copula approach. Finance Res Lett 46(1):102471. https://doi.org/10.1016/j.frl.2021.102471
Umar Z, Bossman A (2023) Quantile connectedness between oil price shocks and exchange rates. Resour Policy 83:103658. https://doi.org/10.1016/j.resourpol.2023.103658
Umar Z, Gubareva M (2020) A time-frequency analysis of the impact of the covid-19 induced panic on the volatility of currency and cryptocurrency markets. J Behav Exp Financ 28:100404. https://doi.org/10.1016/j.jbef.2020.100404
Umar Z, Gubareva M, Naeem M, Akhter A (2021) Return and volatility transmission between oil price shocks and agricultural commodities. PLoS ONE 16(2):1–18. https://doi.org/10.1371/journal.pone.0246886
Wang G-J, Ma X, Wu H (2020) Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests? Res Int Bus Finance 54:101225. https://doi.org/10.1016/j.ribaf.2020.101225
Wei WC (2018) The impact of tether grants on bitcoin. Econ Lett 171:19–22. https://doi.org/10.1016/j.econlet.2018.07.001
Yousaf I, Nekhili R, Gubareva M (2022) Linkages between DeFi assets and conventional currencies: evidence from the COVID-19 pandemic. Int Rev Financ Anal 81:102082. https://doi.org/10.1016/j.irfa.2022.102082
Yousaf I, Gubareva M, Teplova T (2023) Connectedness of non-fungible tokens and conventional cryptocurrencies with metals. N Am J Econ Finance. https://doi.org/10.1016/j.najef.2023.101995

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