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Decentralized and centralized exchanges: Which digital tokens pose a greater contagion risk?

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ABSTRACT

This study explores the impact of trading activity on both centralized exchanges (CEXs) and decentralized exchanges (DEXs) on information transmission patterns between digital and traditional investment assets. Utilizing a quantile connectedness approach, we analyze the relationships among DEX tokens, CEX tokens, and various assets, including Gold, Oil, Bitcoin, REITs, Equity, Bonds, and the US dollar index. Our results reveal that in the lowest quantile, DEX and CEX tokens primarily receive spillovers, while other assets act as the main transmitters. In contrast, in the upper quantile, DEX and CEX tokens become the primary transmitters of spillovers to other assets. These findings hold significant implications for financial portfolio management, as they demonstrate that during a short squeeze period, DEX-CEX tokens exhibit contagious effects on other assets, diminishing the effectiveness of risk management and portfolio strategies. Furthermore, our study suggests that DEX-CEX tokens serve as optimal hedges for oil, offering a cost-effective alternative for hedging Gold and the USD Index.

1. Introduction

The trade of digital assets has increased substantially over the last decade, with centralized exchanges (CEX) acting as the main marketplace for the crypto assets. Recently, decentralized exchanges (DEX) have also gained attention as a viable alternative for investors due to the increased security and anonymity they offer (Aspris et al., 2021). The recent collapses of cryptocurrency exchanges fed into the ongoing debates on whether the extreme volatility of digital assets is posing a threat to global financial stability. In this paper, we aim to explore how the trading activity on CEX and DEX platforms alters the patterns of interconnectedness in the digital asset ecosystem and beyond.

The categorization of digital assets based on their heterogeneous characteristics and blockchain stack position is important for

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understanding the dynamics of information transmission between crypto assets (Corbet et al., 2020; Benedetti and Nikbakht, 2020). Crypto tokens can represent an investor's ownership stake in a business or be used for financial transactions in addition to facilitating exchanges on a blockchain. This implies that, like owners of other securities, token owners can use them to make money through sales or purchases. While cryptocurrencies[1] and crypto tokens share many similarities, cryptocurrencies are designed to be used as a form of payment, a unit of account, and a store of value.

Therefore, the main aim of this paper is to distinguish between tokens traded on CEX and DEX platforms in order to offer a different perspective on how to analyze the information transmission mechanism both inside and outside the crypto asset class. Why does the type of trading platform matter? To support the price discovery process and the provision of liquidity, CEXs have an infrastructure similar to that of the traditional equity markets, which is complete with the same protocols and transaction execution requirements. The primary distinction between CEX and DEX exchanges is that with the former, users retain control over their funds while trading, whereas with the latter, they do not. Beyond just exchanging one digital asset for another, CEX offers a wide range of additional features, including margin trading, crypto derivatives trading, exchange staking, and margin lending, among others. Moreover, CEX allows investors to purchase bitcoin using fiat money. Popular centralized exchanges like Bitstamp, QuadrigaCX, and Coinbase (COIN) are recent examples. These companies had bank accounts, which made it much easier to purchase cryptocurrencies and effectively connected them to the current financial system.

There are some disadvantages to CEX despite its many positive features, such as the potential for sudden changes in financial regulations that could put investors' money at risk. For example, if an exchange is the focus of an investigation, their funds might be momentarily frozen or, in the worst cases, seized. Users of CEX must also verify their identities. In the event of a data breach, their private information might end up being offered for sale on the dark web. Then, they might fall victim to scams, identity theft attempts, or hacking. For instance, the CEX platforms initially seemed to function flawlessly before breaking down. The Mt. Gox attack in 2014 resulted in the theft of over 850,000 bitcoins. Bitstamp was compromised in 2015, and BTC-e was shut down in 2017. Moreover, Gerald Cotten,[2] the CEO and owner of the infamous QuadrigaCX, passed away unexpectedly in 2018 and took the keys to $250 million in cryptocurrency assets with him to his grave. As a result, the exchange was compromised and shut down in 2019 after losing all of its clients' coins.

The recent failures of FTX and Terra Luna proved that the availability of liquidity is essential to the survival of crypto assets and exchanges. Regulators have serious concerns about the capacity of cryptocurrency exchanges to safeguard customers from liquidity constraints and volatility shocks in light of recent crypto crashes (Terra Luna and FTX collapses). Investors seeking a greater level of financial decentralization are attracted to their DEX platforms because CEXs have received harsh criticism for their subpar managerial choices. However, because of the unregulated nature of the cryptocurrency market and the high counterparty risk, investors run a serious risk of losing money. Hackers have reportedly already stolen billions of dollars from renowned exchanges like Bitfinex and Binance, according to recent reports. These attacks on cryptocurrency exchanges have substantially increased price and policy uncertainty in cryptocurrency markets, which consequentially influenced other asset classes (Lucey et al., 2022).

DEXs platforms have become a feasible alternative for investors seeking to overcome the failure of centralized exchanges and looking to transact in digital tokens in a more reliable, secure, and decentralized manner. DEXs make it possible to swap tokens without the need for an intermediary exchange to act as a custodian for their cryptocurrency. There is no doubt that cryptocurrency exchanges have already become more active trading places due to the increased diversity of traded tokens and the variety of instruments available for investors in comparison to the early stages of their existence. It is further expected that DEX platforms will continue growing in size, taking a substantial share of cryptocurrency ecosystem transactions from CEXs. The recent estimates indicate that, in May 2021, trading on DEX platforms exceeded USD150 billion, far outpacing the growth of the rival centralized exchanges.

DEXs and CEXs have coexisted for many years, and many investors have welcomed and used both depending on their preferences for security, affordability, liquidity, risk, and trading opportunities. Keeping in view the unique features offered by both exchanges, the main objective of the current study is to explore the quantile connectedness between decentralized and centralized exchange tokens and other assets. We employ the daily data of three DEX tokens (RUNE-THOR Chain, LRC-Loopring, GNO-Gnosis,) and three CEX tokens (BNB-Binance Coin, LEO-UNUS SED LEO, FTT-FTX Token) from 31 July 2019 to 25 April 2022. We further extend our data period to 30 January 2023 to cover the collapses of Terra Luna and FTX.

We employ Ando et al.'s (2018) technique of quantile-based-connectedness that uses a mix of the quantile VAR and a spillover technique based on the Diebold and Yilmaz (2012) models to examine the link between the median and extreme quantiles. Finally, we use the BEKK–GARCH model for estimating the optimal weights, hedge ratios, and hedging effectiveness for the combination of DEX–other assets and CEX–other assets. The variance and covariances are first estimated using the BEKK–GARCH model for all combinations of DEX–CEX tokens and other assets. Next, following Kroner and Ng (1998), Kroner and Sultan (1993), and Ku et al. (2007), the optimal weights, hedge ratios, and hedging effectiveness are calculated, respectively.

Our paper makes several literary contributions. To the best of our knowledge, this is the first study to examine spillovers between centralized and decentralized exchange tokens and other assets like gold, oil, bitcoin, REITs, stocks, bonds, and the USD index. There is

[1] The most widely used cryptocurrency is Bitcoin (BTCUSD), which is used to send and receive payments using a blockchain. Alternative cryptocurrencies known as "altcoins" were introduced following the enormous success of Bitcoin. The phrase refers to cryptocurrency other than Bitcoin, or alternative coins. They were introduced as improved Bitcoin alternatives that purported to address some of the drawbacks of the original currency. Typical examples of alternative coins include Litecoin (LTCUSD), Dogecoin (DOGEUSD), Namecoin (NAMEUSD), and Bitcoin Cash (BCHUSD). While they have all experienced some success, none have been as well-known as Bitcoin.

[2] Quadriga CEO's widow speaks out over his death and the missing crypto millions | CBC News.

not much research on DEX and CEX tokens; only a few studies specifically examined how these tokens function. The most notable ones in this regard are those by Yousaf and Goodell (2023), in which the authors investigate whether the FTX scandal and its connection to FTT have caused reputational contagion to other tokens like DEX, CEX, NFTs, Defi, Memes, Energy, and Tourism, even tokens with little direct connection to FTT. Their research shows that on the event day (November 8, 2022) almost all token returns were negative. For DEX, NFT, and memes tokens, abnormal returns are negative, whereas CEX tokens experienced mixed results on the event day. The other noteworthy study is one by Aspris et al. (2021), which examines the function of decentralized exchanges and discovers notable variations between CEX and DEX tokens in terms of listing and trading characteristics. Furthermore, they discovered that trading activity significantly increased when DEX tokens were listed on a centralized exchange during the study period. As a result of centralized listings, volume shifts away from decentralized platforms, suggesting that token holders strongly prefer more liquid, deeper markets over the increased security and anonymity offered by decentralized exchanges.

Our paper examines the asymmetric effects of the spillovers between DEX and CEX tokens and other assets by quantifying the spillovers across various quantiles. The asymmetry in financial market spillovers has received a lot of attention in the literature. For instance, Saeed et al. (2021) study the asymmetries in spillovers between green and conventional assets. Naeem et al. (2022) examine the asymmetric spillovers among cryptocurrencies during the COVID-19 pandemic. Anwer et al. (2022) analyze the systemic risk that existed between the markets for energy and non-energy commodities during the COVID-19 pandemic. Our study, which draws on this body of research, offers empirical proof of the asymmetric spillover effects between DEX and CEX tokens and other assets.

According to our findings, at the lowest quantiles, the DEX and CEX tokens are the primary recipients of spillovers, whereas Gold, Oil, Bitcoin, REITs, Equity, Bonds, and the US dollar index are the top transmitters. At the extreme upper quantiles, the DEX and CEX tokens are the primary transmitters of spillovers, whilst other assets are primarily the receivers. Moreover, the different patterns of spillover between DEX–CEX tokens and other assets at various quantiles—the median, the lower extreme, and the upper extreme—further emphasize the importance of researching the DEX–CEX tokens behaviors under various market conditions.

Our findings have significant portfolio management implications since they show that, during a short squeeze period, there are contagious effects of DEX–CEX tokens on traditional assets, thus decreasing the effectiveness of portfolio strategies and risk management. Also, our findings imply that, during tumultuous times like COVID-19, there is a higher degree of interconnectedness between DEX–CEX tokens and other assets. Additionally, based on our analysis, DEX–CEX tokens are the least expensive alternative for hedging Gold and the USD Index while being the greatest option for hedging oil.

The remaining sections of the paper are structured as follows. Literature review is presented in Section 2, data and methodology are covered in Section 3, results and conclusions are presented in Section 4, and the paper is concluded in Section 5.

2. Literature review

The division of digital assets into three categories—currencies, protocols, and centralized applications (dApps)—by Corbet et al. (2020) and Katsiampa et al. (2022) analysis of the co-movements between assets before and during the COVID-19 pandemic are two examples of standard classification techniques. The results reveled the increased role of Ethereum after the COVID-19 crisis in comparison to Bitcoin, driven by the decentralized finance (DeFi) boom and the increased pace of adoption of smart contracts, non-fungible tokens, and other DeFi assets built on Ethereum blockchain (Katsiampa et el., 2022). These results demonstrated the evolution of blockchain ecosystem from the early stages Bitcoin dominance and limited adoption of smart contracts (Drummer and Neumann, 2020; Lacity, 2022) to the current stage of development of highly integrated DeFi information transmission system. The analysis of technological aspects of crypto assets is particularly important to enhance understanding of the risk-return characteristics of the assets, however, empirical finance scholars often ignore these aspects.

Furthermore, technological characteristics of blockchain-based innovations, such as degree of decentralization and anonymity, can help to explain the pace of adoption of blockchain-based assets by various users in cryptocurrency community. The research in this area is growing rapidly but still scarce. Renwick and Gleasure (2020) characterized the privacy attitudes of the different groups of crypto users using Monero privacy coin as a case study. More recently, Dolata and Schwabe (2023) focused on Metaverse and examined technological and social nexus of this emerging ecosystem.

Most of the early cryptocurrency papers have focused on important transactional currencies like Bitcoin, which still dominates in terms of acceptance, price discovery, and trading value in the market (Dwyer, 2015; Dyhrberg et al., 2018; Hu et al., 2019; Wang and Ngene, 2020). Alexander and Heck (2020) were among the first to consider the impact of derivative trading on unregulated crypto exchanges on Bitcoin price discovery. Their findings indicate the insufficient stability and resistance of the bitcoin market against manipulation which is one of the main obstacles in the cryptocurrency markets' development towards a mainstream asset class.

The exponential growth of tokens that may be traded on DEXs suggests a much larger market than is currently recognized, which creates an opportunity to further explore the DEX and CEX impacts on crypto space and beyond. For example, Uniswap, an automated market maker (AMM) is a prominent DEX, having a trading volume that is four times higher than Binance, the leading CEX. In just a short span of time, DEXs have moved from the Bitcoin peripheral to the mainstream. The functioning of the traditional order-book was commonly copied in early attempts to establish a decentralized market; however, this environment has been considerably altered by the advent of liquidity pools, sometimes known as automated market makers. The operational elements of these decentralized protocols, such as registration, verification, execution, and settlement, are well retained even during different stages in the development life cycle. According to Lin (2019), DEXs may be less liquid and riskier because of the greater variety of transaction pairings they can offer.

Some of the prior studies also compare CEX and DEX platforms in terms of their trading volume, liquidity capacity, convenience, transaction costs, and security etc. Among the notable ones are Aspris et al. (2021), who analyzed the decentralized exchanges and provided a comparative analysis between CEX and DEX. They report that cryptocurrency investors showed a preference for the convenience and liquidity of CEXs over the anonymity and security of DEXs.

Pereira et al. (2019) compare the DEX and CEX platforms based on three criteria: transaction costs, technology costs, and community involvement. They discover that DEX platforms are preferable to centralized platforms from a transactional perspective when gains from lower opportunism and uncertainty costs outweigh losses from a higher cost of coordination and complexity. Additionally, they stress that because Artificial Intelligence is an emerging technology, advancements in blockchain protocols and associated complementary innovations have improved the technological infrastructure, lowering the cost and complexity of adopting blockchain protocols. Finally, they show that blockchain-based platforms are preferable to centralized platforms when the intrinsic benefits of the community members outweigh their scanty extrinsic benefits in the short term. With time and community expansion, extrinsic benefits would increase while intrinsic benefits would decrease. If intrinsic and extrinsic benefits are balanced, blockchain-based platforms would be the most beneficial way to organize.

Barbon and Ranaldo (2021) compare the CEX and DEX platforms in terms of market quality. The authors point out that although DEX prices are less efficient than CEX prices, their analysis of transaction costs and departures from the no-arbitrage condition suggests that liquidity in CEXs and DEXs is similar. High exchange fees and the gas costs associated with blockchain transactions are the main obstacles for DEXs, whereas CEXs have significant risks and latency related to delegated custody. Moreover, they quantify conditions for DEXs to surpass CEXs and suggest a stylized model of DEX liquidity provision that maintains an equilibrium between volume, charges, and liquidity.

Alves, P. M. (2023) investigates the price dynamics of Ethereum across CEX and DEX platforms by assessing the size of spillovers between the one of the DEX (Uniswap V2) and three CEX platforms (Binance, Gemini, and Bitstamp). According to his analysis, Binance is a key player in the inter-market price discovery process and has a higher level of gross spillover to other exchanges than Uniswap, Bitstamp, and Gemini. Uniswap, on the other hand, significantly reduces the amount of spillover it provides to other exchanges compared to the other centralized exchanges, and it is significantly more influenced by the other centralized exchanges than they are by it.

Moreover, Pandey (2022) examines the potential for obtaining information from both cryptocurrency exchanges including two DEX (Uniswap and PancakeSwap), and one CEX (Binance) platforms. The author looks at the benefits of each on-site resource and third-party tool that was investigated for data collection. The collected data was then used to examine the pricing, transaction costs, and trading pair management of these exchanges' markets. The results show that while managing on-site resources can be time-consuming and challenging, they also provide a tremendous amount of speed and flexibility. In contrast, third-party resources work well when the required data is available, despite being slower and more expensive. Additionally, the analyses show that while Binance performs better than Uniswap and PancakeSwap in some areas, such as usability and fees, it is comparatively less reliable in others, such as transparency and availability.

Kreppmeier and Laschinger (2023) examine 108 security tokens traded on centralized and decentralized exchanges related to the rapidly evolving area of decentralized finance. There is hardly any underpricing in the market, and it is positively associated with the crypto market sentiment as an external signal. When traded on the secondary market, security tokens generate both extremely positive and negative returns over various short-term time horizons. By disentangling the liquidity situation in the market between centralized and decentralized exchanges, their findings indicate that decentralized marketplaces are less liquid and offer lower barriers to entry, indicating slow market completion.

According to Aspris et al. (2022), there are differences in the trading costs of three market types: centralized exchange (CEX), decentralized exchange (DEX), and automated market makers (AMM), which use liquidity pools and bonding curves to facilitate transactions. According to their research, trading costs on cryptocurrency exchanges are generally higher than those on traditional equity markets. Centralized exchanges are the most affordable place to trade cryptocurrencies, where transactions cost 32bps (basis points) on average (roughly four times as much as stock trading). AMMs are the most expensive; typical trading costs are 130bps. CEXs are roughly half as expensive as DEXs. These alternative asset classes also have significantly higher exchange fees. Trading fees on CEXs range from 2 to 26 bps.

The most recent of several severe crises that impacted cryptocurrency exchanges in recent years was Terra's failure and the subsequent collapse of FTX. According to Jalan and Matkovskyy (2023), contrary to popular belief, the FTX crisis had little effect on the market's systemic and liquidity risks. This is in contrast to earlier negative shocks, which were widely believed to signal the end of the cryptocurrency era. In a similar vein, there has been a much smaller increase in illiquidity than in the past. Overall, the FTX crisis can be seen as the result of a breakdown in corporate governance and regulatory oversight rather than cryptos themselves.

Briola et al. (2023) identify four breakpoints for the crash to analyze the mechanisms that caused the Terra project to fail. According to the authors, the existence of strong selling pressure on this crypto asset on May 5, 2022, may have been the ignition source for the failure of the Terra project. Additionally, the weakening state of the world economy at the moment (caused by the conflict between Russia and Ukraine), bear markets in the major financial indices, and higher federal funds rates may have contributed to "the perfect storm" in the cryptocurrency market. In addition, the Terra project's symbiotic dependence on the Anchor protocol may have increased its exposure to diverse speculative strategies that happened simultaneously by chance. Finally, their result confirms the absence of any herding during bear market conditions.

In similar line, Yousaf and Goodell (2023) examine how the FTX scandal and its link to FTT have negatively affected the reputation of other tokens such as DEX, CEX, NFTs, Defi, Memes, Energy, and Tourism, even tokens with only a tenuous link to FTT. According to their research, almost all token returns on the event day of November 8, 2022, were negative. While CEX tokens had mixed results on the event day, DEX, NFTs, and memes tokens have abnormal returns that are all negative.

3. Data and methodology

3.1. Data

We collect the daily data of three DEX tokens (RUNE-THORChain, LRC-Loopring, GNO-Gnosis,), three CEX tokens (BNB-Binance Coin, LEO-UNUS SED LEO, FTT-FTX Token), and seven other assets (Gold, Oil (WTI), BTC (Bitcoin), REIT (Dow Jones Equity All REIT Index), Equity (MSCI World index), Bond (PIMCO Investment Grade Corporate Bond Index Exchange-Traded Fund), US dollar index) in this study. Prior studies of Aharon and Demir (2021) and Bouri et al. (2021) also use similar other assets and their respective proxies. The sample period started from 31 July 2019 and ended on 25 April 2022. The data of DEX tokens, CEX tokens, and Bitcoin are taken from the website of capitalmarketcap.com, whereas the data of the rest of the assets is extracted from the Bloomberg and S&P Global databases.

One of the limitations of our study is that it requires data from both exchanges and the data must be collected concurrently. The earliest date for which data for these tokens will be available is July 31, 2019, as we need to incorporate the data for three DEX tokens and three CEX tokens used in our analysis from the parallel timeframe. Second, since the decentralized exchanges didn't start functioning until the end of 2018, we are unable to extract data for DEX tokens before that year.

3.2. Methodology

In order to examine the quantile-based interconnectedness between DEX tokens, CEX tokens, and other assets, this study uses the quantile-based-connectedness technique of Ando et al. (2022). To compute the metrices of the quantile connectedness, the infinite order-based vector-moving average specifications of quantile VAR (QVAR) are specified as follows:

$$y_t = \mu(\tau) + \sum_{j}^{p} \Phi_j(\tau) y_{t-j} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} \Omega_i(\tau) u_{t-i} \quad (1)$$

We follow Koop et al. (1996) and Pesaran and Shin (1998) for the "generalized forecast error variance decomposition (GFEVD) with a forecast horizon of H", which is specified as:

$$\Theta_{ij}^{g}(H) = \frac{\sum(\tau)_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^{'} \Omega_h(\tau) \sum(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} \Omega_h(\tau) \sum(\tau) \Omega_h(\tau)^{'} e_i\right)} \quad (2)$$

The unity on the ith position is denoted by e_i along with the zero-vector. The normalization of elements in the de-composition matrix is given below:

$\widetilde{\Theta}_{ij}^{g}(H) = \frac{\Theta_{ij}^{g}(H)}{\sum_{j=1}^{k} \Theta_{ij}^{g}(H)}$, with $\sum_{j=1}^{k} \widetilde{\Theta}_{ij}^{g}.1$ and $\sum_{i,j=1}^{k} \widetilde{\Theta}_{ij}^{g}(H) = 1$. (3).

The GFEVD-based spillover-measures are given below following the Diebold and Yilmaz (2012) model:

$$TO_{j,t} = \sum_{i=1, i \neq j}^{k} \widetilde{\Theta}_{ij,t}^{g}(H) \quad (4)$$

$$FROM_{j,t} = \sum_{i=1, i \neq j}^{k} \widetilde{\Theta}_{ji,t}^{g}(H) \quad (5)$$

$$NET_{j,t} = TO_{j,t} - FROM_{j,t} \quad (6)$$

$$TCI_t = \sum_{i,j=1, i \neq j}^{k} \frac{\widetilde{\Theta}_{ij}^{g}(H)}{k-1} \quad (7)$$

$TO_{j,t}$ shows the effect of variable *j* on variable *I*, and $FROM_{j,t}$ indicates the impact of *i* on *j*. $NET_{j,t}$ represents the disparity between "*TO*" and "*FROM*", and the negative (positive) value refers to the net recipient (transmitter) of spillover. TCI_t denotes the average level of total connectedness. Additionally, we calculate the optimal weights, hedge ratios, and hedging effectiveness by using the BEKK–GARCH model for the combinations of various DEX–other assets and CEX–other assets. The variance and covariances are first determined through BEKK–GARCH models for all the combinations of DEX–CEX tokens and other assets. Second, following Kroner and Ng (1998), Kroner and Sultan (1993), and Ku et al. (2007), we calculate the optimal weights, hedge ratios, and hedging effectiveness, respectively, for all the combinations.

4. Empirical results

4.1. Descriptive statistics

We use the daily data of three DEX tokens (RUNE-THORChain, LRC-Loopring, GNO-Gnosis,), three CEX tokens (BNB-Binance Coin, LEO-UNUS SED LEO, FTT-FTX Token), and seven other assets (Gold, Oil (WTI), BTC (Bitcoin), REIT (Dow Jones Equity All REIT Index), Equity (MSCI World index), Bond (PIMCO Investment Grade Corporate Bond Index Exchange-Traded Fund), US dollar index) in this

Table 1
Summary statistics.

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF
Panel A. DEX tokens								
RUNE	0.0149	0.5622	−0.4250	0.108	0.406	4.983	136.4***	−27.158***
LRC	0.0091	1.0999	−0.4388	0.106	3.310	29.105	21547.5***	−25.504***
GNO	0.0064	0.3901	−0.3487	0.067	0.657	8.668	1005.8***	−26.492***
Panel B. CEX tokens								
BNB	0.0060	0.6976	−0.4190	0.067	1.466	23.390	12606.7***	−17.077***
LEO	0.0029	0.5548	−0.1809	0.042	4.170	52.319	74328.1***	−31.212***
FTT	0.0061	0.3438	−0.2751	0.057	0.738	8.655	1014.7***	−26.245***
Panel C. Other asset classes								
GOLD	0.0005	0.0450	−0.0566	0.010	−0.529	6.656	430.4***	−25.468***
OIL	−0.0031	0.5309	−3.0197	0.132	−17.950	400.604	4734840.0***	−19.743***
BTC	0.0030	0.2111	−0.3717	0.044	−0.568	11.614	2242.7***	−27.566***
REIT	0.0005	0.0899	−0.1794	0.018	−1.546	23.806	13144.5***	−9.844***
EQUITY	0.0005	0.0877	−0.0991	0.013	−1.047	19.102	7832.9***	−7.528***
BOND	−0.0001	0.0706	−0.0496	0.006	0.464	40.821	42520.1***	−10.682***
USD INDEX	0.0001	0.0160	−0.0168	0.004	0.298	5.202	154.6***	−24.113***

Notes: DEX- Decentralized Exchange, CEX- Centralized Exchange, RUNE- THORChain, LRC- Loopring, GNO- Gnosis, BNB- Binance Coin, LEO- UNUS SED LEO, FTT- FTX Token, BTC- Bitcoin, Std. Dev- Standard deviation, ADF- Augmented Dickey Fuller Test. *** indicates the level of significance at 1 per cent.

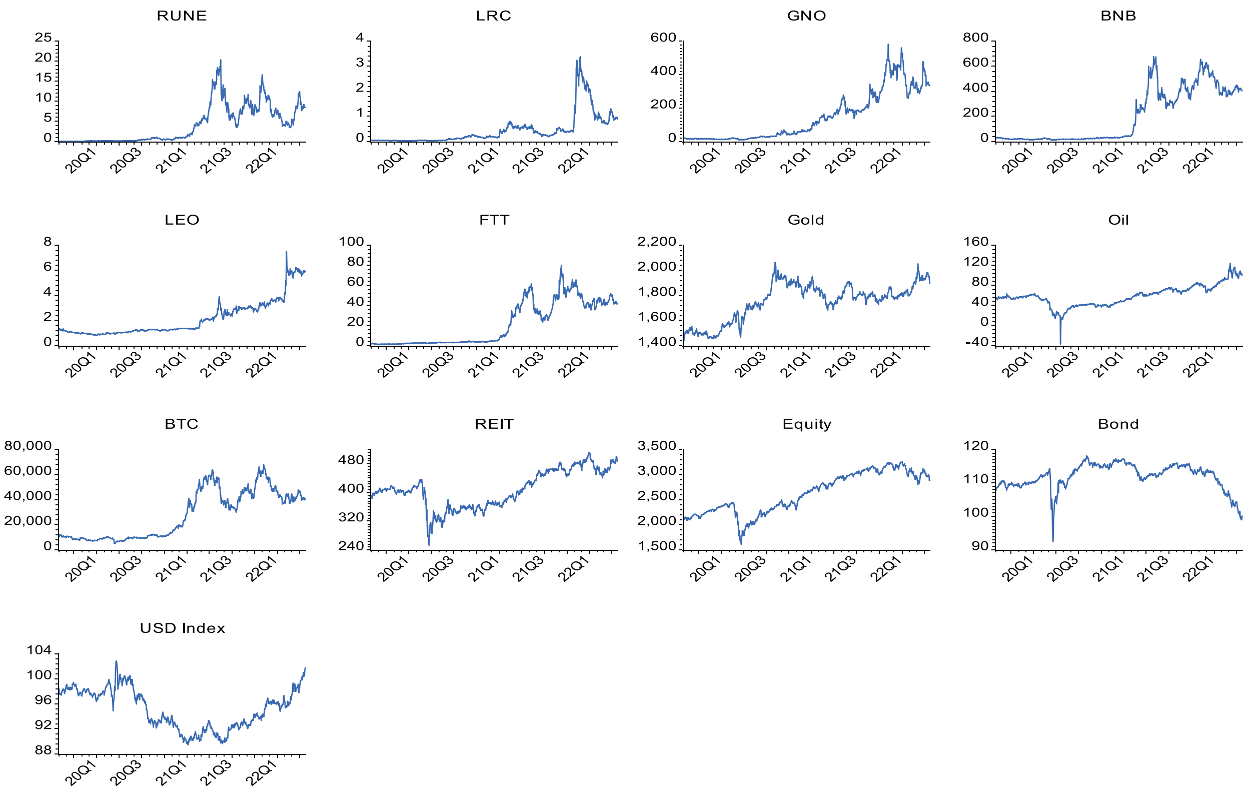

Fig. 1. Prices of DEX tokens, CEX tokens, and other assets.

study. Prior studies of Aharon and Demir (2021) and Bouri et al. (2021) also use similar other assets and their respective proxies. The sample period started from 31 July 2019 and ended on 25 April 2022.[3] The data of DEX tokens, CEX tokens, and Bitcoin are taken from the website of capitalmarketcap.com, whereas the data of the rest of the assets are extracted from the Bloomberg and S&P Global databases.

Table 1 shows the descriptive statistics of all the variables used in the analysis: DEX tokens, CEX tokens, and other assets. The

[3] The FTT-FTX Token data are available from 31 July 2019; therefore, we start our sample period from this date.

Table 2
Unconditional correlations.

		DEX tokens			CEX tokens									
		RUNE	LRC	GNO	BNB	LEO	FTT	GOLD	OIL	BTC	REIT	EQUITY	BOND	USD INDEX
DEX tokens	RUNE	1.000												
	LRC	0.403	1.000											
	GNO	0.361	0.445	1.000										
CEX tokens	BNB	0.434	0.436	0.471	1.000									
	LEO	0.066	0.039	0.099	0.127	1.000								
	FTT	0.408	0.423	0.458	0.651	0.111	1.000							
	GOLD	0.066	0.113	0.065	0.098	−0.033	0.085	1.000						
	OIL	0.055	0.060	−0.032	0.051	−0.004	0.053	0.002	1.000					
	BTC	0.428	0.443	0.547	0.646	0.124	0.658	0.117	0.062	1.000				
	REIT	0.171	0.153	0.164	0.237	0.001	0.126	0.121	0.110	0.242	1.000			
	EQUITY	0.199	0.191	0.252	0.293	0.026	0.212	0.096	0.121	0.347	0.810	1.000		
	BOND	0.040	0.044	0.053	0.103	−0.055	0.033	0.272	0.050	0.123	0.291	0.243	1.000	
	USD INDEX	−0.069	−0.090	−0.082	−0.069	0.052	−0.115	−0.327	−0.010	−0.089	−0.118	−0.177	−0.270	1.000

Notes: DEX- Decentralized Exchange, CEX- Centralized Exchange, RUNE- THORChain, LRC- Loopring, GNO- Gnosis, BNB- Binance Coin, LEO- UNUS SED LEO, FTT- FTX Token, BTC- Bitcoin.

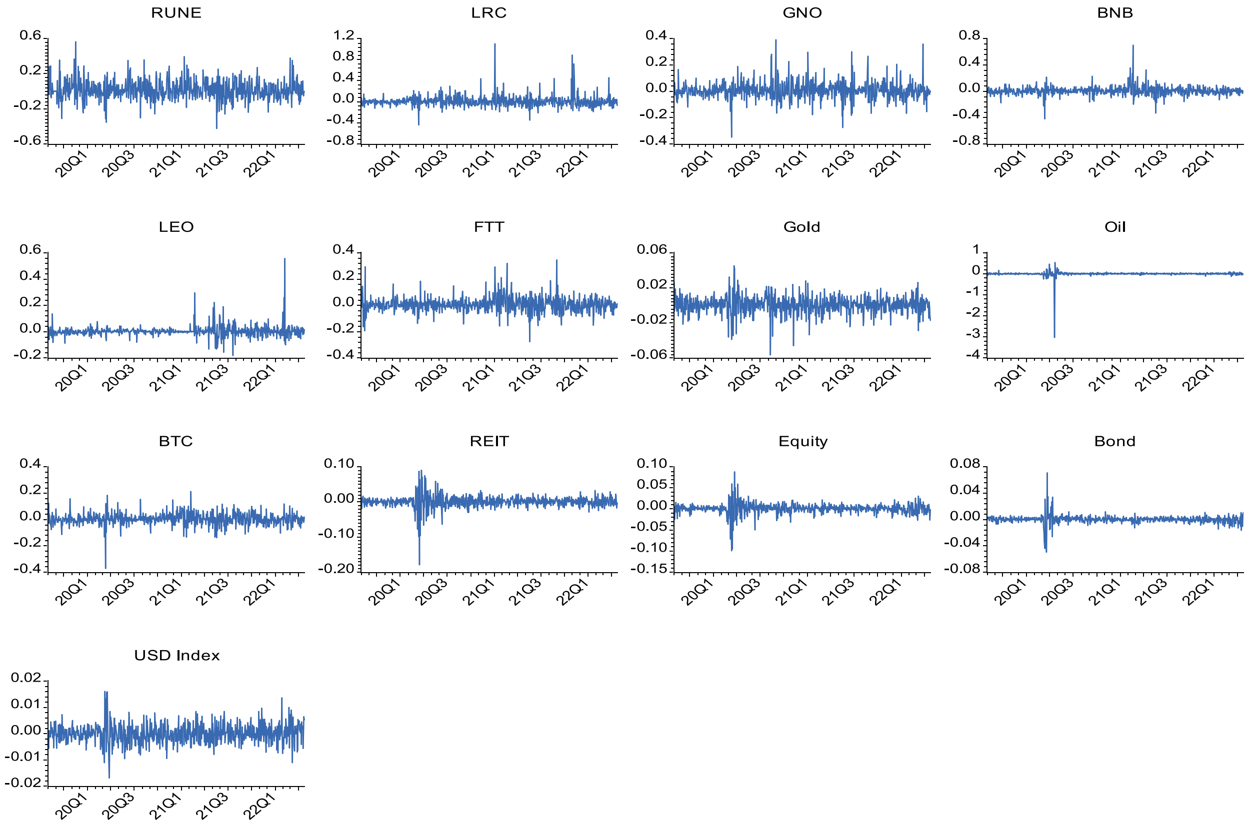

Fig. 2. Returns of DEX tokens, CEX tokens, and other assets.

average returns show that the DEX and CEX tokens outperform the Gold, Oil, BTC, REIT, Equity, Bond, and USD Index. This is hardly unexpected considering that 2021 is seen as the “DEX take-off” phase, with reported trading of over USD150 billion exceeding that of competing centralized exchanges (Aspris et al., 2021). However, compared to the DEX and CEX tokens, the unconditional volatilities of Gold, BTC, REIT, Equity, Bond, and USD Index are lower.

The RUNE tokens have the highest average returns out of all markets, while the BOND has the lowest; nevertheless, Oil has the most unconditional volatility, while USD Index has the lowest. When compared to the other assets taken into account in the analysis, DEX and CEX tokens offer better rewards at a higher risk. The profiles of risk and returns of the DEX and CEX tokens compared to conventional assets like Gold, Oil, BTC, REIT, Equity, Bonds, and US dollar index are very different. The skewness is positive for all DEX and CEX tokens; however, Gold, Oil, BTC, and REITs have a negative skewness. The kurtosis is higher than 3 for all DEX tokens, CEX tokens, and other assets. The Jarque–Berra statistics indicate the non-normality of the series. Also, there are no traces of a unit root in any of the series as shown by the Augmented Dickey Fuller test.

The daily closing prices of the DEX tokens, CEX tokens, and all other assets during the entire sample period are shown in Fig. 1. We analyze the peaks and troughs in prices of all DEX and CEX tokens during the first quarter of 2021 until the first quarter of 2022 as this period represents the high trading activity in these exchanges. We also find a sharp decline in the prices of all other assets except for the USD Index during year the first and second quarters of 2020 corroborating the first and second waves of the COVID-19 pandemic. Similarly of note is the excessive increase in prices of the BTC during 2021 that is in line with the 2021 cryptocurrency market bubble timeline (Flitter, 2022). The price of USD Index exhibited a falling trend, while the prices of all other assets witnessed an uptick until the last quarter of 2021. The majority of asset prices increased during this time period, reflecting the market’s response to the potential pandemic recovery; however, higher oil prices during this period indicate the surplus oil demand during this time. During the first quarter of 2022, the prices of all assets depict a volatile behavior in response to the Russia–Ukraine military conflict.

Table 2 provides the correlations among DEX tokens, CEX tokens, and other assets. The correlations among DEX tokens, CEX tokens, and Bitcoin are high as these assets belong to digital assets classes. The weak correlation between the DEX and CEX tokens and other assets, including Gold, BTC, REITs, Equity, Bonds, and USD Index, shows that investors can maximize the benefits of diversification by including the DEX and CEX tokens in their portfolios of Gold, BTC, REITs, Equity, Bonds, and USD Index. The correlation is positive among DEX tokens, CEX tokens, and other assets, except the USD Index, which has a negative correlation with all of these other assets.

The time-varying returns are also illustrated in Fig. 2, which provides evidence of the volatility clustering in all markets during different timeframes. Moreover, the peaks of volatilities can be observed after 1 January 2020 in Gold, BTC, REIT, Equity, Bond, and

Table 3
Static return spillover at the means using the Diebold and Yilmaz (2012) approach.

		DEX tokens			CEX tokens										
		RUNE	LRC	GNO	BNB	LEO	FTT	Gold	Oil	BTC	REIT	Equity	Bond	USD.Index	From
DEX tokens	RUNE	45.84	9.25	6.89	10.63	1.55	8.95	1.15	0.76	9.17	2.03	2.44	0.45	0.90	54.16
	LRC	8.51	41.67	10.51	10.89	1.33	8.95	1.64	0.77	9.28	1.77	2.09	0.83	1.76	58.33
	GNO	6.10	9.92	40.95	11.52	0.82	10.42	1.29	0.55	12.37	1.52	2.82	0.58	1.15	59.05
CEX tokens	BNB	7.78	8.34	9.31	32.48	1.78	15.10	1.48	0.65	14.48	2.61	3.83	0.80	1.36	67.52
	LEO	2.06	2.50	1.62	4.57	74.98	2.46	0.88	0.78	2.55	1.73	2.67	1.43	1.78	25.02
	FTT	6.94	7.48	8.77	14.89	1.30	33.74	1.52	0.73	16.45	1.98	3.22	0.72	2.25	66.26
	Gold	1.75	1.66	1.76	2.81	1.18	3.07	56.38	2.30	3.83	1.99	3.81	8.07	11.39	43.62
	Oil	1.94	2.28	2.09	1.37	0.49	1.70	2.42	71.31	1.60	2.61	7.23	2.57	2.39	28.69
	BTC	7.13	7.61	10.41	14.53	0.96	16.29	2.06	0.47	31.32	2.14	4.09	1.00	2.00	68.68
	REIT	1.99	2.39	2.29	3.93	1.03	2.20	2.38	1.94	3.27	50.13	22.42	3.27	2.77	49.87
	Equity	2.32	2.33	3.35	5.10	1.20	3.69	3.38	4.40	5.23	18.81	42.01	2.93	5.24	57.99
	Bond	0.75	1.40	1.13	1.79	1.01	1.50	8.22	2.05	2.15	3.80	3.94	67.35	4.92	32.65
	USD.Index	1.30	2.51	2.49	3.64	1.10	3.83	11.27	2.04	3.68	4.83	8.70	6.31	48.30	51.70
	To Others	48.57	57.67	60.62	85.67	13.75	78.16	37.69	17.43	84.07	45.81	67.24	28.97	37.90	663.54
	Inc.Own	94.41	99.35	101.56	118.16	88.72	111.90	94.07	88.74	115.38	95.95	109.25	96.32	86.20	TCI
	Net	−5.59	−0.65	1.56	**18.16**	−11.28	**11.90**	−5.93	−11.26	15.38	−4.05	9.25	−3.68	−13.80	51.04

Notes: DEX- Decentralized Exchange, CEX- Centralized Exchange, RUNE- THORChain, LRC- Loopring, GNO- Gnosis, BNB- Binance Coin, LEO- UNUS SED LEO, FTT- FTX Token, BTC- Bitcoin.

Table 4
Static return spillover at the median quantile (Q = 0.50).

		DEX tokens			CEX Tokens										
		RUNE	LRC	GNO	BNB	LEO	FTT	Gold	Oil	BTC	REIT	Equity	Bond	USD.Index	From
DEX tokens	RUNE	47.48	9.21	6.45	9.98	1.50	8.14	1.33	0.93	8.55	2.10	2.38	0.81	1.13	52.52
	LRC	8.43	43.66	10.28	10.34	1.23	8.56	1.45	0.62	9.15	1.72	2.21	0.87	1.48	56.34
	GNO	5.73	9.81	42.14	11.12	0.93	9.84	1.36	0.68	12.02	1.68	3.02	0.77	0.89	57.86
CEX tokens	BNB	7.51	8.12	9.05	34.28	1.51	14.81	1.23	0.75	14.63	2.36	3.64	0.83	1.30	65.72
	LEO	1.31	1.71	1.33	3.34	80.99	2.13	0.97	0.59	2.20	1.31	1.79	1.04	1.30	19.01
	FTT	6.61	7.44	8.74	14.78	1.15	35.50	1.45	0.82	16.56	1.55	2.84	0.60	1.96	64.50
	Gold	1.36	1.73	1.85	2.72	1.04	2.55	58.56	2.18	3.40	2.02	3.60	7.98	11.02	41.44
	Oil	1.51	1.92	1.40	1.51	0.72	1.87	1.90	74.59	1.47	2.29	6.63	2.09	2.11	25.41
	BTC	6.89	7.49	10.34	14.67	0.89	16.08	1.83	0.51	32.89	1.95	3.89	0.91	1.68	67.11
	REIT	2.22	2.53	2.56	3.50	1.43	2.09	2.51	2.24	2.93	50.43	21.61	3.20	2.75	49.57
	Equity	2.34	2.08	3.24	4.65	1.24	3.32	2.96	4.73	4.67	18.61	44.38	2.88	4.88	55.62
	Bond	0.74	1.29	1.28	1.85	1.06	1.48	7.46	2.16	2.01	3.74	4.20	68.03	4.71	31.97
	USD.Index	1.40	2.47	2.62	3.84	1.15	3.34	10.48	2.09	3.33	5.18	9.12	5.58	49.39	50.61
	To Others	46.04	55.79	59.14	82.30	13.82	74.21	34.94	18.31	80.92	44.52	64.92	27.56	35.20	637.67
	Inc.Own	93.52	99.45	101.29	116.58	94.81	109.71	93.50	92.90	113.81	94.96	109.30	95.59	84.60	TCI
	Net	−6.48	−0.55	1.29	**16.58**	−5.19	**9.71**	−6.50	−7.10	13.81	−5.04	9.30	−4.41	−15.40	49.05

Notes: DEX- Decentralized Exchange, CEX- Centralized Exchange, RUNE- THORChain, LRC- Loopring, GNO- Gnosis, BNB- Binance Coin, LEO- UNUS SED LEO, FTT- FTX Token, BTC- Bitcoin.

Table 5
Static return spillover at the extreme lower quantile (Q = 0.05).

		DEX tokens			CEX tokens										
		RUNE	LRC	GNO	BNB	LEO	FTT	Gold	Oil	BTC	REIT	Equity	Bond	USD.Index	From
DEX tokens	RUNE	9.71	7.02	7.61	7.81	7.20	8.19	7.59	6.70	7.68	7.84	7.90	7.70	7.06	90.29
	LRC	7.84	10.40	8.02	7.75	6.77	8.00	7.56	6.55	7.63	7.73	7.59	7.55	6.60	89.60
	GNO	7.83	7.04	10.20	7.65	7.06	7.91	7.45	6.64	7.72	7.89	7.77	7.89	6.95	89.80
CEX tokens	BNB	7.77	7.02	7.68	9.78	7.20	8.65	7.05	6.55	7.84	7.82	7.93	7.66	7.05	90.22
	LEO	7.35	6.40	7.38	7.17	10.82	7.67	7.85	6.78	7.12	8.03	8.01	8.08	7.35	89.18
	FTT	7.51	6.92	7.70	8.11	7.24	9.69	7.39	6.57	8.21	7.98	7.84	7.83	7.01	90.31
	Gold	7.34	6.61	7.19	7.08	7.00	7.44	10.91	7.11	7.16	8.15	8.00	9.09	6.92	89.09
	Oil	7.35	6.51	7.34	6.84	6.85	7.26	7.83	10.90	6.91	8.23	8.78	8.15	7.03	89.10
	BTC	7.75	6.92	7.79	8.16	7.19	8.63	7.27	6.59	9.30	7.61	8.01	7.75	7.03	90.70
	REIT	6.96	6.56	7.25	7.23	6.95	7.42	7.85	7.08	7.12	10.91	9.00	8.68	6.98	89.09
	Equity	7.00	6.56	7.13	7.24	7.24	7.61	8.02	7.18	7.20	8.72	10.79	8.39	6.93	89.21
	Bond	7.10	6.39	7.33	7.05	6.90	7.30	8.53	6.97	7.05	8.36	8.59	11.45	6.97	88.55
	USD.Index	7.28	6.25	7.45	7.20	7.44	7.28	7.65	6.95	7.16	8.08	8.51	8.45	10.29	89.71
	To Others	89.08	80.19	89.87	89.30	85.01	93.37	92.05	81.68	88.79	96.45	97.95	97.22	83.88	1164.84
	Inc.Own	98.79	90.59	100.07	99.09	95.83	103.06	102.96	92.59	98.09	107.37	108.73	108.67	94.18	TCI
	Net	−1.21	−9.41	0.07	−0.91	−4.17	3.06	2.96	−7.41	−1.91	7.37	8.73	8.67	−5.82	89.60

Notes: DEX- Decentralized Exchange, CEX- Centralized Exchange, RUNE- THORChain, LRC- Loopring, GNO- Gnosis, BNB- Binance Coin, LEO- UNUS SED LEO, FTT- FTX Token, BTC- Bitcoin.

Table 6
Static return spillover at the extreme upper quantile (Q = 0.95).

		DEX tokens			CEX tokens										
		RUNE	LRC	GNO	BNB	LEO	FTT	Gold	Oil	BTC	REIT	Equity	Bond	USD.Index	From
DEX tokens	RUNE	9.84	7.69	8.07	9.48	7.03	8.97	6.82	5.95	7.65	7.27	7.01	6.84	7.38	90.16
	LRC	7.48	9.67	8.44	9.14	6.67	9.28	6.82	6.01	8.12	7.18	6.89	6.94	7.34	90.33
	GNO	7.40	7.80	10.64	9.82	6.45	9.70	6.61	5.85	8.16	7.22	6.85	6.39	7.11	89.36
CEX tokens	BNB	7.08	7.49	8.20	13.61	6.73	9.66	6.59	6.10	7.82	7.15	6.74	6.29	6.55	86.39
	LEO	7.14	7.70	7.91	8.14	9.89	8.43	7.11	6.20	7.55	7.50	7.14	7.24	8.04	90.11
	FTT	6.92	7.60	8.20	10.93	6.73	11.46	6.61	5.92	8.19	6.97	6.93	6.60	6.95	88.54
	Gold	6.99	7.32	7.39	9.25	6.80	8.61	10.92	6.19	7.39	7.54	7.30	7.62	6.65	89.08
	Oil	6.79	7.50	7.20	8.17	6.41	8.45	6.81	11.28	7.70	7.56	7.73	7.10	7.30	88.72
	BTC	7.05	7.85	7.80	9.77	6.75	9.49	6.85	5.93	9.98	7.22	7.17	7.05	7.09	90.02
	REIT	6.74	7.17	7.29	9.63	6.75	8.79	6.97	6.29	7.22	10.48	8.43	7.21	7.05	89.52
	Equity	6.79	7.33	7.71	9.88	6.34	8.98	6.70	6.40	7.41	8.66	10.04	6.89	6.87	89.96
	Bond	7.07	7.31	7.55	8.21	6.64	8.09	7.99	6.46	7.60	7.80	7.25	11.05	6.99	88.95
	USD.Index	7.14	7.46	7.71	8.19	7.22	8.28	6.97	6.15	7.68	7.44	7.46	7.50	10.80	89.20
	To Others	84.58	90.22	93.46	110.60	80.52	106.74	82.85	73.46	92.49	89.53	86.90	83.69	85.30	1160.34
	Inc.Own	94.41	99.88	104.09	124.21	90.41	118.20	93.78	84.74	102.47	100.01	96.95	94.74	96.10	TCI
	Net	−5.59	−0.12	**4.09**	**24.21**	−9.59	**18.20**	−6.22	−15.26	2.47	0.01	−3.05	−5.26	−3.90	89.26

Notes: DEX- Decentralized Exchange, CEX- Centralized Exchange, RUNE- THORChain, LRC- Loopring, GNO- Gnosis, BNB- Binance Coin, LEO- UNUS SED LEO, FTT- FTX Token, BTC- Bitcoin.

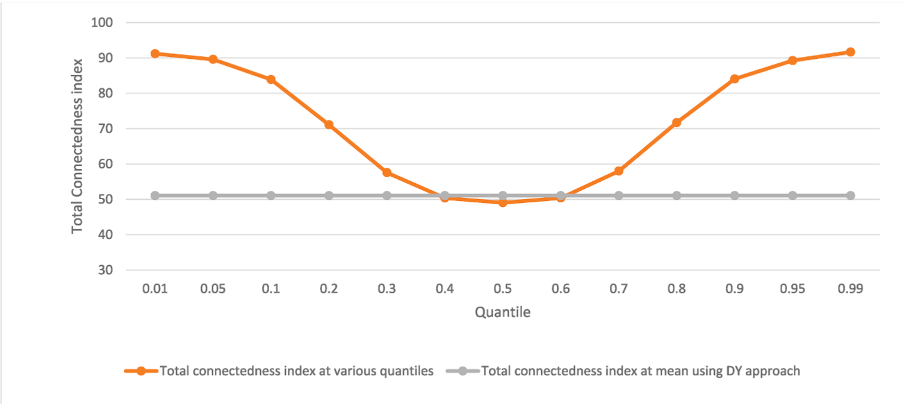

Fig. 3. Total connectedness over various quantiles.

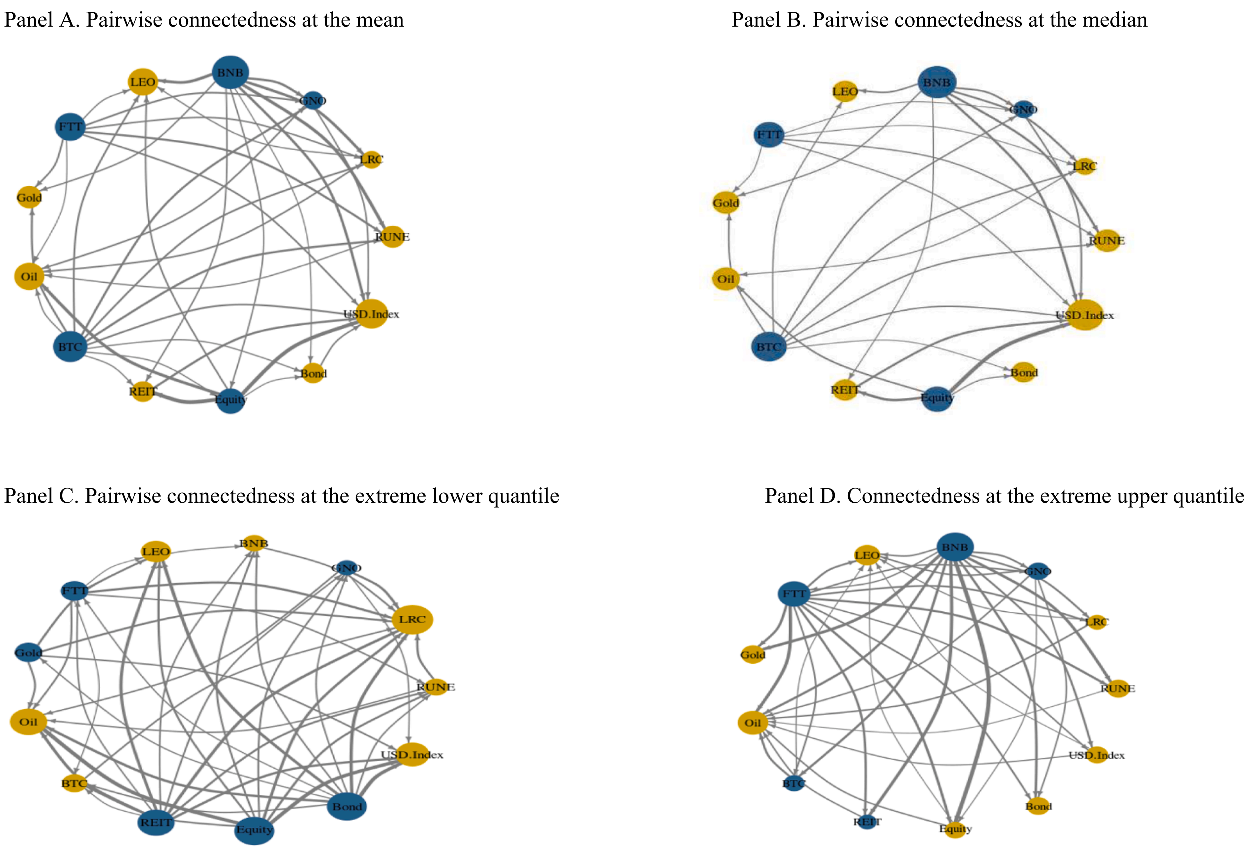

Fig. 4. Static Pairwise connectedness.

USD Index, showing that the COVID-19 pandemic considerably affected all assets. However, the DEX and CEX tokens are least affected during the same period.

4.2. Static spillovers at different quantiles

The findings of the static spillovers at different quantiles—conditional mean, conditional median, extreme lower, and extreme upper quantiles, respectively—are reported in Tables 3–6. Following some earlier works, such as Bouri et al., (2020; 2021) and Liu et al. (2021), among others, and employing the Diebold and Yilmaz (2012) suggested methodology, the conditional mean connectedness is first estimated using a mean-based VAR framework. In relation to this outcome, the connectedness results at different

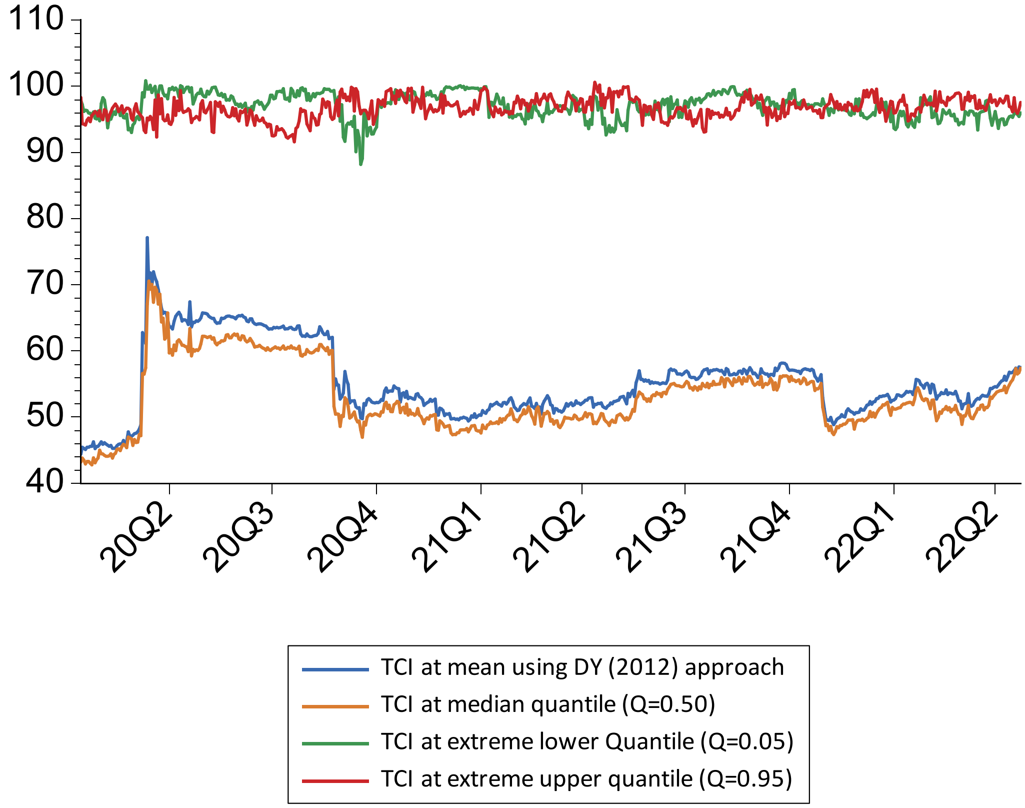

Fig. 5. Time-varying TCI.

quantiles (Q = 0.50, Q = 0.05 Q = 0.95) are assessed.

Table 3 provides the static mean connectedness results between DEX tokens, CEX tokens, and other assets. There is a sizeable level of connectedness among DEX tokens, CEX tokens, and other assets of 51.04 %, as indicated by the total connectedness index (TCI) in the last column. The return spillovers from each market to the system are shown in the '*To Others*' row. The findings indicate that maximum return transmissions to the system come from CEX tokens—i.e., BNB (85.67 %) and FTT (78.16 %)—which are comparable to cryptocurrency market leader Bitcoin (84.07 %). The lowest return transmissions come from LEO (13.75 %), Oil (17.43 %), and Bond (28.97 %). The DEX tokens are net recipients of return spillovers, with the exception of GNO (1.56 %); however, the value of the net spillover is too marginal to claim any influential power on other assets in the system. The results also show that the oil and Bond markets are not reliable predictors of DEX tokens and CEX tokens because they only have a minor impact on these tokens, with the exception of LEO tokens. The low connectedness between traditional assets and tokens suggests some diversification opportunities available for investors.

The outcomes of return spillovers from the system to each asset are shown in the '*From*' column. The results show that BTC (68.68 %), BNB (67.52 %), and FTT (66.26 %) achieved the system's highest return effects. The system transmits the lowest return effects to the LEO (25.02 %), Oil (28.69 %), and Bond (32.65 %) markets, suggesting that the influence of DEX and CEX tokens on those markets is minimal. Overall, the results of oil and Bond markets' return spillovers to the system show that DEX tokens and CEX tokens are poorly tied to the oil and Bond markets, suggesting that these tokens can be used as a hedge against these markets. According to these results, the LEO token seems to be relatively decoupled from other digital and traditional assets, and returns are mainly influenced by its own innovations (74.98 %).

The row '*Net*' describes the results of net return spillovers; a positive (negative) value for net return spillover denotes a net transmitter (recipient). The largest net recipients of the return spillovers are the USD Index (-13.80 %), LEO tokens (-11.28 %), and Oil (-11.28 %), whereas the largest net transmitters of the return effects are BNB (18.16 %), BTC (15.38 %), and FTT (11.90 %).

4.3. Quantile connectedness measures

Table 4 reports that the TCI is 49.05 % at the median (Q = 0.50) quantile. In terms of TCI, connectedness to and from the system, and net connectedness, the results are like those of the mean connectedness shown in Table 3 and corroborate the findings of previous studies by Yousaf et al. (2022), Liu et al. (2021), Bouri et al. (2020), and Ji et al. (2019).

After calculating conditional mean and median connectedness, we next calculated the static return connectedness at the extreme lower quantile (Q = 0.050) and extreme upper quantile (Q = 0.95) in Tables 5 and 6. The connectivity of the assets improves when

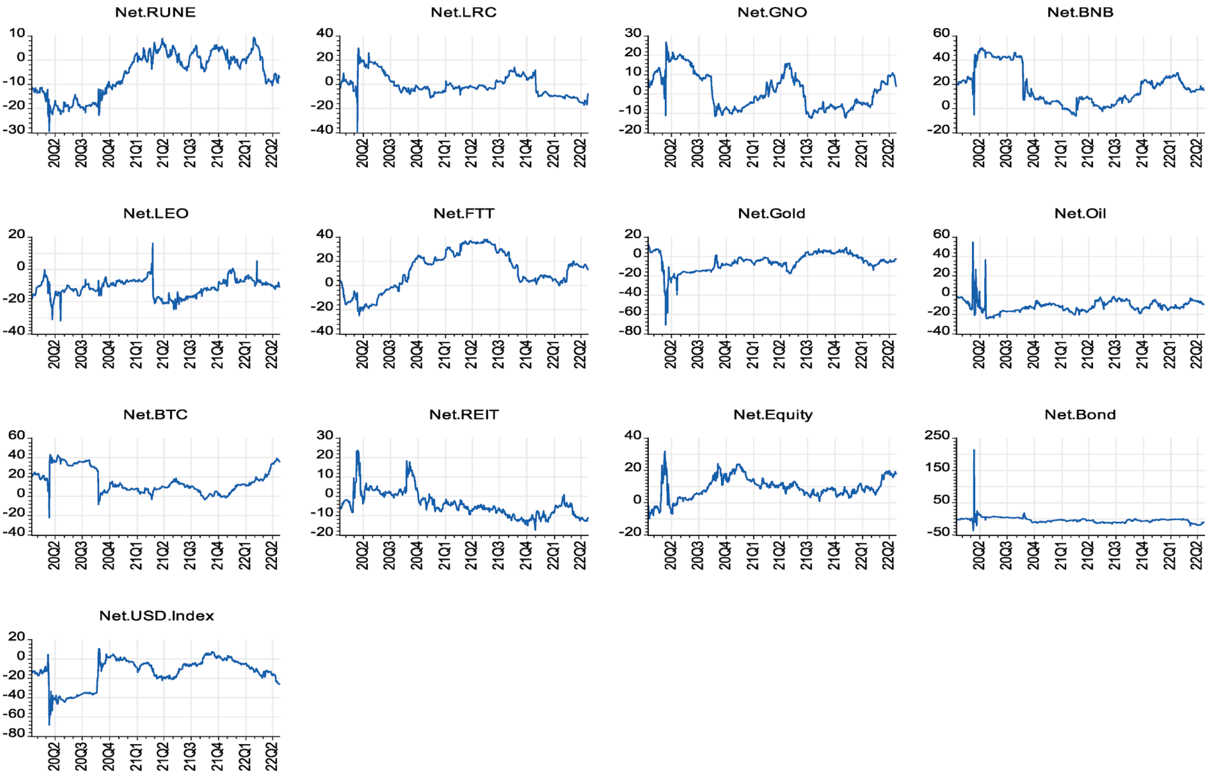

Fig. 6. Time-varying net directional spillovers at the mean using the Diebold and Yilmaz (2012) approach.

there are major market moves, as evidenced by the total connectedness being 89.6 % at the extreme lower quantile and 89.26 % at the extreme higher quantile. Fig. 3 makes this clear by showing that the left and right quantiles are more related overall than the median quantile.

Equity and Bonds, at the extreme lower quantile, are the largest spillovers' transmitter to the system, according to the connectedness values of 97.97 % and 97.22 %, respectively, as represented by '*To*' in the third to last row of Table 5. These findings are in line with the literature supporting the fact that investors switch to safety and liquidity options in tumultuous market conditions. The remaining assets in the system experience almost the same amounts of system spillovers as the interconnectedness shown by the last column '*From*' for all assets' ranges between 88.55 % and 90.31 %. Our research also reveals that, at the lower extreme quantile, stock, bonds, and REIT are clearly the biggest net transmitters of spillovers, whilst LRC tokens, Oil, and the USD Index are significantly the biggest net receivers. This is consistent with the findings of Cho et al. (2016) and Baur and Lucey, (2010), who discussed the "flights to quality" phenomenon which occurs when investors transfer funds during down-market conditions from riskier assets to safer ones.

Our findings suggest that the DEX and CEX tokens contributed more to the system at the upper extreme quantile. It is evident from the results in Table 6 that the BNB and FTT tokens contributed the most spillovers to the system (110.60 % and 106.74 %, respectively). Both tokens are CEX tokens, and their influential power is substantially higher than that of the DEX tokens, which contribute less to the system. LEO is yet again an exception, and, similar to the results reported earlier, this CEX token is the biggest net spillover recipient. We find that all assets experience almost the same amounts of system spillovers, because, as shown in the last column '*From*', the connectedness ranges between 86.39 % and 90.16 %. The greater degree of interconnectedness at the extreme upper and extreme lower quantiles corroborates the earlier research demonstrating a rise in financial contagion during extreme market situations (Farid et al., 2022; Naeem et al., 2022; Pham et al., 2022).

The network of connectedness across the assets at the extreme lower quantile is shown in panel C and at the extreme upper quantile is shown in panel D of Fig. 4. While other assets (Equity, Bond, REIT, and Gold) are spillover transmitters, the DEX and CEX tokens (LRC, RUNE, LEO, and BNB) are spillover receivers in the case of the lower extreme quantile. Also, in the case of the lower extreme quantile, the DEX and CEX tokens are closely related, with FTT transferring the most spillovers to BNB, RUNE, and LRC tokens. The DEX and CEX tokens (BNB, FTT, and GNO) are spillover transmitters at the extreme upper quantile, whereas other assets (Gold, Oil, Equity, Bonds and USD Index) are spillover receivers. Moreover, the thicker arrows in Fig. 4D compared to the thin arrows in Fig. 4A–C show that these assets at the extreme upper quantile are more interconnected. Similarly, according to our findings, the DEX and CEX tokens are the primary recipients of spillovers at the lower quantiles, whereas other assets are mostly the transmitters. Furthermore, during periods of significant upward market movement, such as a market short-squeeze episode, this connectivity becomes stronger.

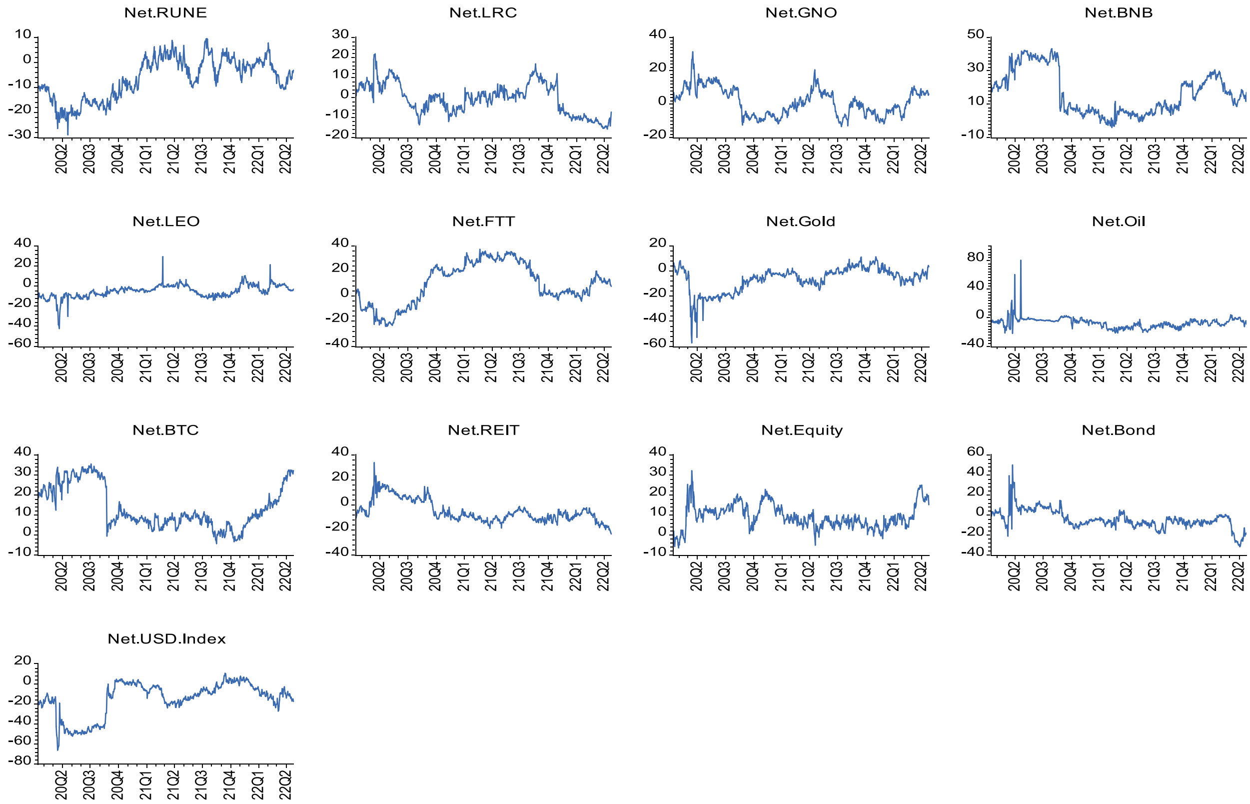

Fig. 7. Time-varying net directional spillovers at the median (Q = 0.50).

4.4. Dynamic spillovers at different quantiles

Next, we look into time-varying spillovers between DEX–CEX tokens and other assets. The dynamic total spillover at different quantiles is displayed in Fig. 5. It is clear that all of the quantiles' total spillover indices change over time. The total spillover indexes vary between 45 % and 75 % at the median quantile and between 95 % and 100 % at the extreme quantiles over the course of the sample period. This shows a high level of market integration, with spillovers being more pronounced at the extreme upper and lower quantiles in comparison to the mean and median quantiles. Additionally, in the case of the mean and median quantiles, the TCI increases by about 60 % to 70 % from the start to the end of 2020, while in the case of both extreme quantiles (upper and below), connectedness is still above 90 %. This is the period when COVID-19 was at its worst and the World Health Organization (WHO) declared it a pandemic. These findings are supported by the conclusions of Yousaf and Yarovaya (2022) and Umar et al. (2022) that the increased return connectedness during 2020 was as a result of fears related to the pandemic, which resulted in lockdowns throughout the world.

Figs. 6 and 7 show the net spillovers of each asset at the mean and median. These results are consistent with the results of Fig. 5 in the manner that the net return spillovers vary in every market over time. Moving on to the dynamics of the net spillovers, at the mean level, on average, the majority of DEX tokens, CEX tokens, Gold, Oil, and USD Index are the net recipients of the return spillovers, as shown in Fig. 6. In contrast, BTC and Equity are the main net transmitters of spillovers, with a peak in transmission during the COVID-19 pandemic. This shows that there are more spillovers from BTC and Equity to DEX and CEX tokens, Gold, Oil, and the USD Index than there are in the reverse direction, particularly during the global health crisis. Gold and the USD Index are generally the main recipients of return spillovers, particularly during the global pandemic. Additionally, in the first quarter of 2020, there was the highest transmission of return spillovers, with BTC and Equity serving as the primary net transmitters. Another interesting finding is that whereas most assets serve as net receivers of spillover during the worldwide pandemic outbreak in 2020, bonds serve as a large transmitter, illustrating the phenomenon of "flight to quality" as bonds are perceived as having higher "quality" and, therefore, are considered a safe investment. However, a significant decrease in bond values occurs in the second quarter of 2022, primarily because of the FED[4]'s decision regarding raising interest rates on bonds in response to rising inflation. At the median quantile, we discover a similar relationship across all the assets as depicted in Fig. 7.

At the extreme lower and extreme upper quantiles, the net spillovers are shown in Figs. 8 and 9. Overall, these figures exhibit

[4] https://www.forbes.com/sites/qai/2022/09/22/is-this-the-worst-year-ever-for-bonds/?sh=65baccd2b4fe.

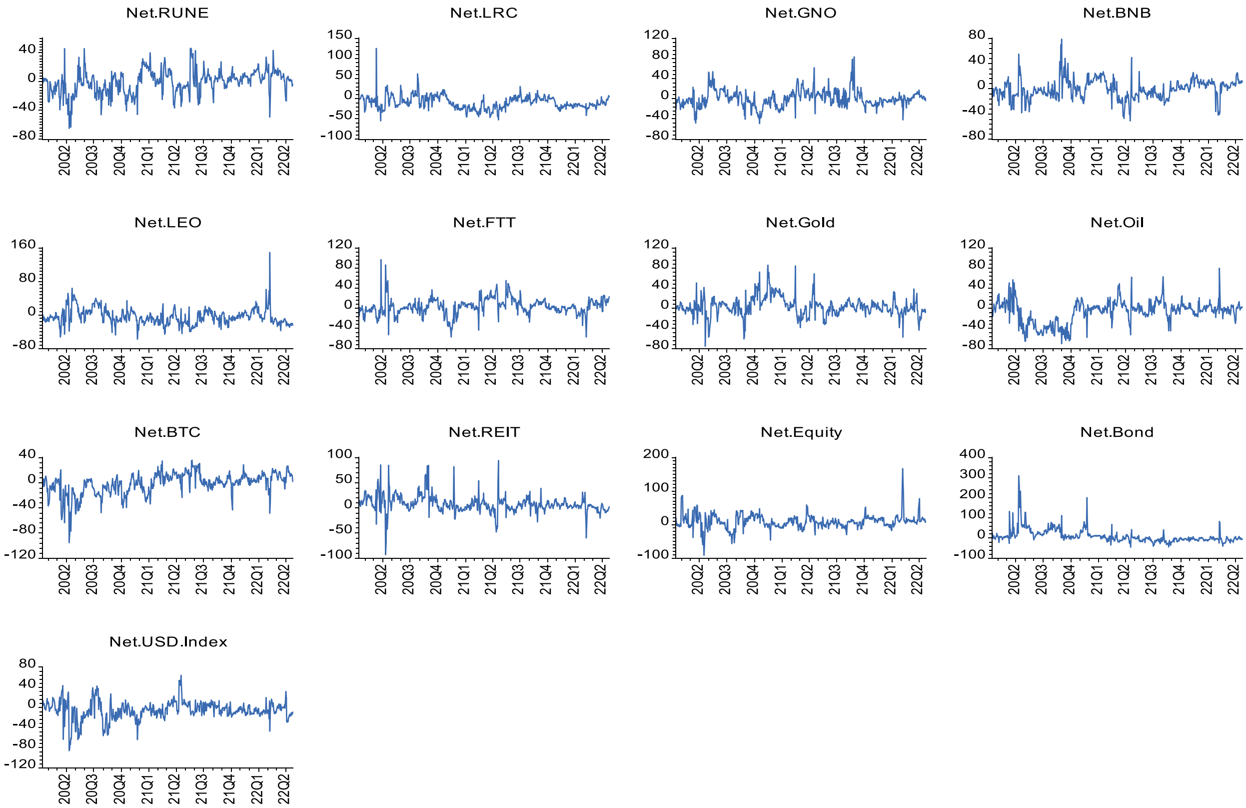

Fig. 8. Time-varying net directional spillovers at the extreme lower quantile (Q = 0.05).

patterns resembling those in Figs. 6 and 7, indicating that the spillover effects between DEX tokens, CEX tokens, and other assets are time varying. More frequently, in comparison to Figs. 6 and 7, the net spillovers in Figs. 8 and 9 oscillated between positive and negative values, which is consistent with the shifting functions of these systems as transmitters and receivers of spillovers during the course of the sample period. Accordingly, it can be inferred that spillovers at the extreme quantiles are more unpredictable than spillovers at the mean or median quantiles. We find that towards the beginning of 2022, net spillovers for BTC are increasing at the upper quantile, while those for Equity and LEO tokens are decreasing at the lower quantile. This demonstrates the "flight to quality" phenomenon that was common at the time as the onset of the Russia–Ukraine war increased market uncertainty (Khalfaoui et al., 2022). While Gold and Equity experiences a severe decline during the first quarter of 2021, net spillovers for BNB and FTT tokens enjoy a high surge, before returning to their mean value by the end of 2021.

The relative tail dependence (RTD) spillovers are displayed in Fig. 10. The difference between the TCI at the extreme upper quantile and the TCI at the extreme lower quantile is shown by the RTD. The RTD shifts between positive and negative values over time (mainly during the first three quarters of 2020). In line with Bouri et al. (2020) at the start of the sample period, RTD values started to decline, signaling a higher degree of dependency in the lower quantile as a result of COVID-19 outbreak. However, rising (positive) values for the relative tail dependence in the last quarter of 2020 indicate a growing connectedness, suggesting that short squeezes on the DEX token and CEX token cause significant contagion in other assets.

The market contagion and interdependence differ during bubbles and normal times as shown by some previous studies. Gharib et al. (2021) report two instances of the infectious effects of bubbles in the Gold and Oil markets: one is the COVID-19 outbreak and the second is the imbalance in oil prices during 2014–2015. According to Bazán-Palomino (2022), who examined the adoption of cryptocurrencies, the cryptocurrency booms of 2017 and 2021 changed the dependencies among various cryptocurrencies. Similar to this, Geuder et al. (2019) examined the behavior of Bitcoin and identified the traits of the Bitcoin Bubble. In December 2017, this cryptocurrency saw a significant price increase, with coin prices reaching about USD 20,000. From the end of 2021 until the end of the sample period, the RTD fluctuates between positive and negative values.

Our research has increased understanding of how extreme returns spillovers spread throughout the network of linkages between DEX tokens, CEX tokens, and other assets. In line with past studies by Bouri et al., (2020, 2021) and Liu et al. (2021), we find evidence of asymmetry and higher return connectedness in the lower and upper tails. Our research involves the first implementation of a quantile-based approach for the system between DEX tokens, CEX tokens, and other assets. Additionally, in agreement with Bouri et al. (2021), we see that conditional connectedness grows stronger in unpredictable circumstances like the COVID-19 pandemic, which has been supported by recent research for different assets and alternative approaches.

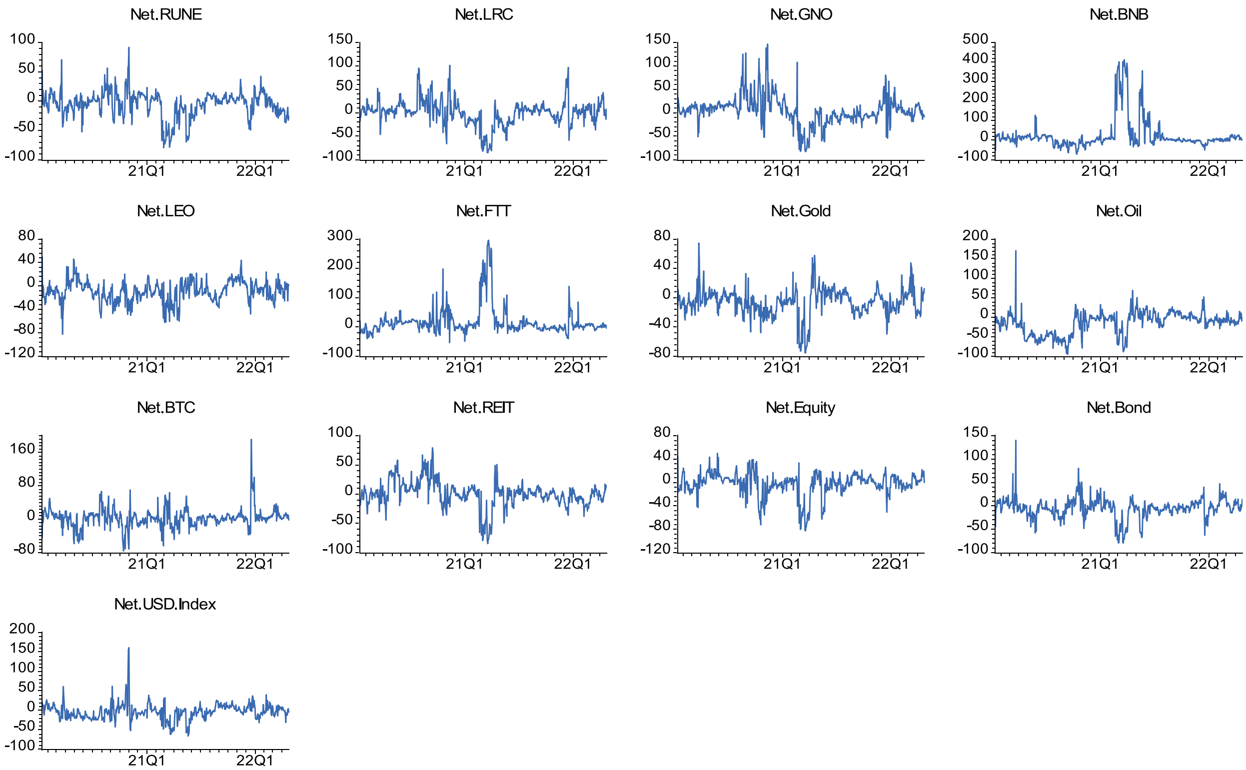

Fig. 9. Time-varying net directional spillovers at the extreme upper quantile (Q = 0.95).

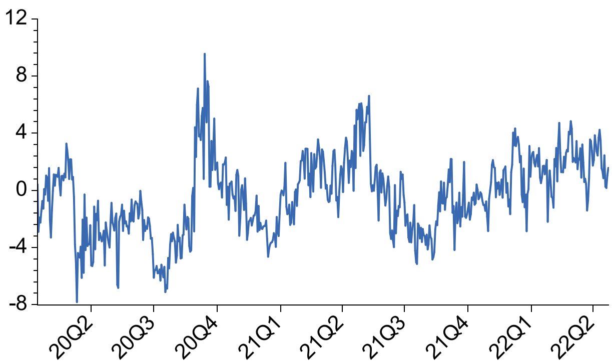

Fig. 10. Relative tail dependence ($TCI_{Q=0.95} - TCI_{Q=0.05}$).

4.5. Robustness test

To test the robustness of our results, we estimate the static and time-varying spillovers using the sample period from 31 July 2019 to 30 January 2023. This new sample period also includes the FTX collapse period—the FTX collapse happened on 8 November 2022— so we consider the effect of this event as well. Tables A1 to A4 provide the static connectedness between DEX, CEX, and other markets at the mean, median, upper extreme quantile, and lower extreme quantile. The total connectedness is not much different from the updated sample period and is the sample period most used in this study; however, the total connectedness is slightly higher in the updated sample period (including the FTX event period) at the mean, median, upper, and lower quantiles. The time-varying spillover, in Fig. A1, shows that there is no big difference in total spillover trend before and after the FTX collapse period. However, the total spillover index shows a short period of abrupt change only on the FTX collapse event day, but no prominent impact was observed after that day. This shows that the FTX collapse does not significantly influence the connectedness between DEX, CEX, and other assets classes, which makes our results robust with the updated sample period.

Table 7
Portfolio design and hedging effectiveness for the combinations of other asset–DEX and other asset–CEX.

	Optimal weight (w_t^{OD})	Hedge ratio (β_t^{OD})	Hedging effectiveness (HE)		Optimal weight w_t^{OC}	Hedge ratio (β_t^{OC})	Hedging effectiveness (HE)
Panel A. Other asset–RUNE				**Panel D.** Other asset–BNB			
Gold/RUNE	1.00	0.01	0.00	Gold/BNB	0.98	0.02	0.01
Oil/RUNE	0.86	0.06	0.78	Oil/BNB	0.72	0.13	0.92
BTC/RUNE	0.98	0.17	−0.04	BTC/BNB	0.76	0.56	0.02
REIT/RUNE	0.99	0.02	−0.05	REIT/BNB	0.97	0.06	−0.02
Equity/RUNE	1.00	0.02	0.00	Equity/BNB	0.99	0.05	−0.05
Bond/RUNE	0.99	0.00	0.05	Bond/BNB	1.00	0.01	0.00
USD.Index/RUNE	1.00	0.00	0.00	USD.Index/BNB	0.99	−0.01	0.02
Panel B. Other asset–LRC				**Panel E.** Other asset–LEO			
Gold/LRC	1.00	0.01	0.00	Gold/LEO	0.86	0.00	0.20
Oil/LRC	0.85	0.06	0.76	Oil/LEO	0.48	−0.04	0.98
BTC/LRC	0.98	0.21	0.00	BTC/LEO	0.31	0.26	0.61
REIT/LRC	0.99	0.02	0.00	REIT/LEO	0.80	0.01	0.61
Equity/LRC	1.00	0.02	0.00	Equity/LEO	0.87	0.01	0.45
Bond/LRC	1.00	0.00	0.00	Bond/LEO	0.96	−0.01	0.42
USD.Index/LRC	0.99	0.00	0.01	USD.Index/LEO	0.98	0.00	0.04
Panel C. Other asset–GNO				**Panel F.** Other asset–FTT			
Gold/GNO	0.98	0.01	0.01	Gold/FTT	0.98	0.02	0.00
Oil/GNO	0.75	−0.04	0.89	Oil/FTT	0.70	0.12	0.94
BTC/GNO	0.84	0.42	0.05	BTC/FTT	0.73	0.57	0.04
REIT/GNO	0.97	0.04	0.05	REIT/FTT	0.95	0.04	0.18
Equity/GNO	0.99	0.04	−0.02	Equity/FTT	0.99	0.05	0.02
Bond/GNO	0.99	0.01	0.14	Bond/FTT	0.99	0.01	0.14
USD.Index/GNO	0.99	0.00	0.01	USD.Index/FTT	0.99	−0.01	0.03

Notes: DEX- Decentralized Exchange, CEX- Centralized Exchange, RUNE- THORChain, LRC- Loopring, GNO- Gnosis, BNB- Binance Coin, LEO- UNUS SED LEO, FTT- FTX Token, BTC- Bitcoin. w_t^{OD} is the weight of *O* (other asset) in a one-dollar portfolio of O (other asset) and D (DEX token) at time t, whereas 1-w_t^{OD} is the weight of *D* (DEX token) in a one-dollar portfolio of O (other asset) and D (DEX token) at time t. w_t^{OC} is the weight of *O* (other asset) in a one-dollar portfolio of O (other asset) and C (CEX token) at time t, whereas 1-w_t^{OC} is the weight of *C* (CEX token) in a one-dollar portfolio of O (other asset) and C (CEX token) at time t. β_t^{OD} represents the hedge ratio, which shows that a short position in the *D* (DEX token) asset can hedge a long position in the *O* (other asset) asset. β_t^{OC} represents the hedge ratio, which shows that a short position in the *C* (CEX token) asset can hedge a long position in the *O* (other asset) asset. A higher HE score shows a higher risk reduction, and vice versa. Hedging effectiveness score is calculated for the optimal weight-based portfolios.

4.6. Portfolio implications

The optimal weights, hedge ratios, and hedging efficiency for the combinations of CEX tokens–other assets (Panels A to C) and DEX tokens–other assets (Panels D to F) are shown in Table 7. Gold/RUNE, Equity/RUNE, USD Index/RUNE, Gold/LRC, Equity/LRC, and Bond/LRC have the highest optimal weights (100 %) among the different combinations of DEX tokens, indicating that for the one-dollar portfolio, investors would be indifferent and could select either Gold or RUNE, or any other combination mentioned above.

The REIT/RUNE (Equity/LRC, Equity/GNO) combination has an optimal weight of 0.99, meaning that for a one-dollar portfolio of REIT (Equity) and RUNE (LRC, GNO), investors should place 99 cents in REIT (Equity) and the remaining cent in the RUNE (LRC, GNO) tokens. In the one-dollar portfolio of Oil /GNO, investors should put 25 cents in the GNO because it has the lowest weight (0.75) among different combinations.

Similarly, in the case of CEX tokens, the combination of Bond and BNB has the maximum weight (100 %), indicating that investors would be agnostic and could choose either Bond or BNB tokens for the one-dollar portfolio. The ideal weight for the combinations of USD Index/BNB (Equity/FTT, Bond/FTT, USD-Index/FTT) is 0.99, meaning that for a portfolio of USD Index (Equity, Bond, USD Index) and BNB (FTT) valued at one dollar, investors should place 99 cents in USD Index (Equity, Bond, USD Index) and the remaining one cent in the BNB (FTT) token. The optimal weight for the BTC/LEO combination is the lowest (0.31), meaning that for every one dollar invested in BTC and LEO portfolio, investors should put 31 cents into LEO.

Overall, all optimal weights are 1 or very close to 1 in the majority of the combinations of DEX tokens–other assets and CEX tokens–other assets, indicating that, when combined with undiversified portfolios of Gold, Oil, BTC, REIT, Equity, Bond, and US dollar index, DEX and CEX tokens offer investors very limited opportunities for diversification. This outcome supports the findings of Aliu et al. (2021) and Aliu et al. (2022), which show that portfolios based solely on equity stocks are less risky than those based only on

Table A1
Static return spillover at the means using the Diebold and Yilmaz (2012) approach [Sample period: 31 July 2019 to 30 January 2023].

		DEX tokens			CEX tokens										
		RUNE	LRC	GNO	BNB	LEO	FTT	Gold	Oil	BTC	REIT	Equity	Bond	USD.Index	From
DEX tokens	RUNE	40.05	9.89	8.11	11.32	1.51	9.42	1.21	0.66	10.69	2.25	3.15	0.63	1.12	59.95
	LRC	9.53	37.47	10.49	11.7	1.26	9.36	1.73	0.78	10.08	2.1	2.73	0.92	1.87	62.53
	GNO	7.53	9.91	36.56	11.73	1.12	10.69	1.27	0.63	13.03	1.98	3.63	0.66	1.26	63.44
CEX tokens	BNB	8.91	9.26	9.78	29.64	1.65	14.33	1.62	0.59	14.61	2.84	4.29	0.93	1.55	70.36
	LEO	2.47	2.78	2.52	4.34	72.28	3.13	0.73	0.76	3.50	1.61	2.78	1.41	1.70	27.72
	FTT	7.93	8.18	9.5	14.48	1.46	31.44	1.36	0.76	16.17	2.07	3.80	0.74	2.11	68.56
	Gold	1.84	2.04	1.77	3.13	0.97	2.67	54.3	3.75	3.60	2.83	4.56	7.79	10.76	45.70
	Oil	1.83	2.33	2.31	1.69	0.60	2.02	4.23	68.79	2.04	2.56	6.15	2.87	2.58	31.21
	BTC	8.54	8.18	10.97	14.37	1.23	15.42	1.93	0.54	28.34	2.49	4.84	1.09	2.07	71.66
	REIT	2.71	2.8	3.11	4.32	1.06	2.52	2.64	1.56	4.07	45.62	21.64	4.46	3.46	54.38
	Equity	3.25	3.01	4.30	5.55	1.28	4.35	3.52	3.50	6.28	17.99	37.84	3.33	5.78	62.16
	Bond	1.11	1.58	1.33	2.06	0.98	1.53	8.24	2.04	2.41	5.72	4.97	62.52	5.51	37.48
	USD.Index	1.74	2.86	2.86	3.82	1.09	3.62	10.46	1.97	3.94	5.74	9.78	6.35	45.77	54.23
	To Others	57.41	62.83	67.05	88.50	14.20	79.06	38.94	17.53	90.43	50.19	72.31	31.17	39.77	709.39
	Inc.Own	97.46	100.31	103.6	118.14	86.47	110.5	93.23	86.32	118.77	95.81	110.15	93.69	85.54	TCI
	Net	−2.54	0.31	3.60	18.14	−13.53	10.5	−6.77	−13.68	18.77	−4.19	10.15	−6.31	−14.46	54.57

Notes: DEX- Decentralized Exchange, CEX- Centralized Exchange, RUNE- THORChain, LRC- Loopring, GNO- Gnosis, BNB- Binance Coin, LEO- UNUS SED LEO, FTT- FTX Token, BTC- Bitcoin.

Table A2
Static return spillover at the median quantile (Q = 0.50) [Sample period: 31 July 2019 to 30 January 2023].

		DEX tokens			CEX tokens										
		RUNE	LRC	GNO	BNB	LEO	FTT	Gold	Oil	BTC	REIT	Equity	Bond	USD.Index	From
DEX tokens	RUNE	41.68	9.9	7.74	10.82	1.44	8.7	1.29	0.81	10.11	2.25	3.06	0.87	1.32	58.32
	LRC	9.5	39.24	10.31	11.23	1.14	9.01	1.55	0.66	9.95	2	2.84	0.96	1.6	60.76
	GNO	7.2	9.85	37.79	11.41	1.16	10.1	1.34	0.74	12.72	2.1	3.75	0.77	1.06	62.21
CEX tokens	BNB	8.7	9.09	9.56	31.22	1.4	14.1	1.31	0.68	14.81	2.65	4.11	0.94	1.43	68.78
	LEO	1.81	1.92	2.3	3.33	77.5	2.8	0.82	0.6	3.13	1.38	2.19	0.98	1.26	22.5
	FTT	7.69	8.2	9.37	14.48	1.3	33.22	1.21	0.8	16.32	1.66	3.41	0.6	1.74	66.78
	Gold	1.55	2.31	1.95	3.24	0.86	2.37	55.83	3.51	3.4	2.73	4.24	7.51	10.49	44.17
	Oil	1.51	2.11	1.82	1.82	0.72	2.25	3.66	71.17	1.88	2.4	5.65	2.54	2.47	28.83
	BTC	8.32	8.1	10.89	14.58	1.14	15.27	1.68	0.56	29.77	2.28	4.63	1.01	1.77	70.23
	REIT	2.85	2.97	3.42	4.06	1.47	2.31	2.74	1.82	3.72	45.98	20.63	4.44	3.6	54.02
	Equity	3.33	2.88	4.23	5.26	1.46	3.96	3.19	3.8	5.8	17.56	39.83	3.26	5.45	60.17
	Bond	1.13	1.56	1.51	2.07	1.04	1.59	7.66	2.48	2.36	5.43	5.3	62.47	5.41	37.53
	USD.Index	2.02	2.94	3.08	3.94	1.11	3.31	9.9	2	3.68	5.77	10.02	5.55	46.67	53.33
	To Others	55.61	61.83	66.17	86.25	14.25	75.77	36.36	18.45	87.88	48.2	69.83	29.44	37.61	687.63
	Inc.Own	97.28	101.07	103.96	117.47	91.75	108.98	92.19	89.62	117.64	94.19	109.66	91.9	84.28	TCI
	Net	−2.72	1.07	3.96	17.47	−8.25	8.98	−7.81	−10.38	17.64	−5.81	9.66	−8.1	−15.72	52.89

Notes: DEX- Decentralized Exchange, CEX- Centralized Exchange, RUNE- THORChain, LRC- Loopring, GNO- Gnosis, BNB- Binance Coin, LEO- UNUS SED LEO, FTT- FTX Token, BTC- Bitcoin.

Table A3
Static return spillover at the extreme lower quantile (Q = 0.05) [Sample period: 31 July2019 to 30 January 2023].

		DEX tokens			CEX tokens										
		RUNE	LRC	GNO	BNB	LEO	FTT	Gold	Oil	BTC	REIT	Equity	Bond	USD.Index	From
DEX tokens	RUNE	9.36	7.18	7.59	7.62	7.54	8.34	7.39	6.64	8.12	7.56	8.01	7.38	7.27	90.64
	LRC	7.84	9.84	7.83	7.55	7.19	8.23	7.35	6.56	8.06	7.44	7.8	7.3	7	90.16
	GNO	7.77	7.18	9.63	7.52	7.55	8.2	7.29	6.59	8.11	7.51	7.95	7.48	7.22	90.37
CEX tokens	BNB	7.72	7.13	7.65	9.28	7.68	8.71	7.04	6.54	8.14	7.5	8.06	7.3	7.26	90.72
	LEO	7.31	6.57	7.35	7.1	10.9	7.82	7.61	6.73	7.43	7.66	8.23	7.71	7.55	89.1
	FTT	7.58	7.11	7.63	7.92	7.35	9.82	7.19	6.62	8.53	7.65	7.92	7.46	7.22	90.18
	Gold	7.36	6.8	7.1	7.04	7.23	7.66	10.47	7.17	7.49	7.86	8.11	8.6	7.11	89.53
	Oil	7.3	6.78	7.18	6.8	7.24	7.55	7.74	10.31	7.29	7.85	8.83	7.79	7.34	89.69
	BTC	7.74	7.08	7.59	7.86	7.5	8.75	7.18	6.53	9.46	7.34	8.18	7.48	7.29	90.54
	REIT	7.09	6.78	7.2	7.05	7.32	7.71	7.65	6.96	7.6	10.2	9.03	8.25	7.16	89.8
	Equity	7.06	6.71	7.14	7.16	7.68	7.8	7.77	7.03	7.59	8.29	10.63	8.02	7.12	89.37
	Bond	7.18	6.65	7.23	7.05	7.2	7.57	8.17	6.9	7.45	8.05	8.61	10.71	7.22	89.29
	USD.Index	7.19	6.54	7.3	7.14	7.71	7.52	7.57	7	7.46	7.71	8.47	7.99	10.39	89.61
	To Others	89.15	82.53	88.79	87.82	89.2	95.86	89.96	81.26	93.27	92.44	99.21	92.77	86.75	1169.01
	Inc.Own	98.51	92.37	98.42	97.1	100.1	105.68	100.43	91.57	102.73	102.64	109.84	103.48	97.13	TCI
	Net	−1.49	−7.63	−1.58	−2.9	0.1	5.68	0.43	−8.43	2.73	2.64	9.84	3.48	−2.87	89.92

Notes: DEX- Decentralized Exchange, CEX- Centralized Exchange, RUNE- THORChain, LRC- Loopring, GNO- Gnosis, BNB- Binance Coin, LEO- UNUS SED LEO, FTT- FTX Token, BTC- Bitcoin.

Table A4
Static return spillover at the extreme upper quantile (Q = 0.95) [Sample period: 31 July 2019 to 30 January 2023].

		DEX tokens			CEX tokens										
		RUNE	LRC	GNO	BNB	LEO	FTT	Gold	Oil	BTC	REIT	Equity	Bond	USD.Index	From
DEX tokens	RUNE	9.43	7.99	7.8	8.78	7.64	8.39	7.01	6.25	7.64	7.32	7.21	6.95	7.60	90.57
	LRC	7.54	9.7	8.12	8.57	7.3	8.58	6.98	6.39	7.9	7.22	7.12	7.00	7.58	90.3
	GNO	7.46	8.06	10.01	9.08	6.98	8.94	6.91	6.16	8.02	7.26	7.12	6.61	7.40	89.99
CEX tokens	BNB	7.21	7.93	8	12.24	7.19	8.98	6.81	6.32	7.85	7.21	7.02	6.48	6.76	87.76
	LEO	7.17	7.89	7.6	7.7	10.1	7.92	7.32	6.56	7.48	7.44	7.23	7.4	8.20	89.9
	FTT	7.1	7.78	8.03	10.05	7.05	10.73	6.86	6.29	8.14	6.95	7.13	6.78	7.11	89.27
	Gold	6.95	7.47	7.23	8.61	7.1	7.93	10.95	6.71	7.28	7.55	7.43	7.77	7.02	89.05
	Oil	6.84	7.72	7.14	7.74	6.9	7.9	7.22	10.93	7.51	7.51	7.7	7.24	7.66	89.07
	BTC	7.27	8.07	7.67	9.14	7.15	8.82	7.05	6.2	9.58	7.28	7.35	7.12	7.30	90.42
	REIT	6.88	7.47	7.3	8.93	7.16	8.19	7.13	6.46	7.25	10.18	8.43	7.39	7.23	89.82
	Equity	6.92	7.54	7.63	9.09	6.78	8.37	6.93	6.72	7.46	8.59	9.83	7.05	7.09	90.17
	Bond	7.06	7.51	7.38	7.8	7.03	7.7	8.08	6.8	7.49	7.81	7.36	10.75	7.23	89.25
	USD.Index	7.16	7.67	7.51	7.7	7.82	7.69	7.21	6.52	7.48	7.44	7.51	7.49	10.81	89.19
	To Others	85.53	93.09	91.41	103.18	86.11	99.41	85.5	77.38	91.5	89.58	88.61	85.29	88.18	1164.76
	Inc.Own	94.96	102.79	101.42	115.42	96.21	110.13	96.45	88.31	101.08	99.76	98.44	96.04	98.99	TCI
	Net	−5.04	2.79	1.42	15.42	−3.79	10.13	−3.55	−11.69	1.08	−0.24	−1.56	−3.96	−1.01	89.60

Notes: DEX- Decentralized Exchange, CEX- Centralized Exchange, RUNE- THORChain, LRC- Loopring, GNO- Gnosis, BNB- Binance Coin, LEO- UNUS SED LEO, FTT- FTX Token, BTC- Bitcoin.

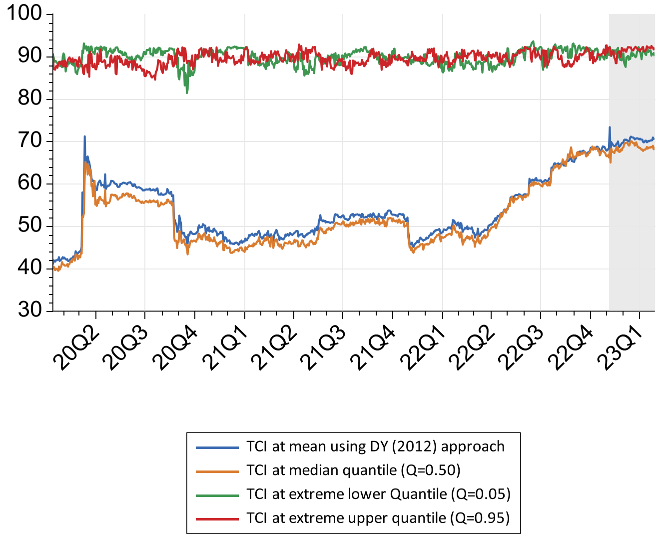

Fig. A1. Time-varying TCI. [Highlighted area is showing after the FTX collapse period].

cryptocurrencies. These findings are in line with the fundamental theories of portfolios, which hold that riskier portfolios generate higher returns and vice versa and offer helpful advice for DEX and CEX token investors who prefer to lower portfolio risk by including stocks, commodities, digital currency, and fiat money.

The hedge ratios of the DEX (CEX) token with other assets are presented in the second column of Table 7. The highest hedge ratio for BTC/GNO (BTC/FTT) is 0.42(0.57), indicating that a long position of one dollar in BTC can be hedged with 0.58 (0.43) cent short position in GNO(FTT). The hedge ratios between the Gold/RUNE, Gold/LRC, Gold/GNO, and Bond/GNO combinations are lowest, indicating that RUNE, LRC, and GNO tokens are cheap options for hedging Gold and bond. For the remaining CEX tokens–other assets, the lowest hedge ratios are between the combinations of Bond/BNB, REIT/LEO, Equity/LEO, and Bond/FTT, inferring that the BNB, LEO, and FTT are the cheapest hedge for REIT, Equity, and Bond. Overall, the DEX and CEX tokens are the cheapest options for hedging Gold, Bond, and Equity.

The final column of Table 7 shows hedging effectiveness (HE) of the selected asset's pairs. Among the combinations of DEX tokens–other assets, the hedge effectiveness is highest between Oil/RUNE, Oil/LRC, and Oil/GNO combinations and minimal for the combinations of USD Index/LRC, Gold/GNO, and USD Index/GNO. Similarly, among the combinations of CEX tokens–other assets, the hedge effectiveness is highest between Oil/BNB, Oil/LEO, and Oil/FTT combinations and minimal for the combinations of Gold/BNB, USD Index/BNB, USD Index/LEO, and USD Index/FTT.

These findings have important ramifications for investors who want to safeguard themselves from the spillover effects of Gold, Oil, BTC, REITs, Equity, Bonds, and the US dollar index. Our, results suggest that the DEX and CEX tokens are the most preferable hedge for Oil, whereas the DEX and CEX tokens provide the least possible hedging opportunities to the investors of Gold and the USD index.

5. Conclusion

This paper employs a quantile connectedness approach to examine the relationships between CEXs and DEX tokens with other asset classes. According to our findings, in the case of the lower extreme quantile, the DEX and CEX tokens are the main recipients of spillovers, whereas Gold, Oil, Bitcoin, REITs, stocks, bonds, and the US dollar index are the primary transmitters. This demonstrates the propensity of investors to gravitate toward quality during exceptionally bad market conditions. At the extreme upper quantile, the DEX and CEX tokens are the primary transmitters of spillovers indicating that the market short squeezes and price bubbles in these assets tend to spread to other markets.

Comparing DEX and CEX tokens, our results indicate that CEX tokens are more influential than DEX tokens, and hence more contagious. The spillover effects from CEX tokens to other assets are higher during the extreme market conditions, which makes CEX tokens a more serious threat to financial stability in comparison to DEX tokens. One notable exception is the LEO tokens that are traded on centralized exchanges but do not transmit any returns spillovers to other markets compared to other CEX tokens in our sample.

The robustness test demonstrates that the FTX collapse has not altered the patterns of interconnectedness and our results remain intact. This robustness test further supports our base results suggesting a higher connectedness between digital tokens and other assets during the extreme market conditions, e.g., the FTX collapse, which is evidenced by the higher total spillover index as well. We contribute to the corpus of knowledge by conducting the first investigation on the connection between DEX and CEX tokens and other financial assets at various quantiles. The patterns of spillover between DEX–CEX tokens and other assets that we observed at the lower extreme quantile, median quantile, and upper extreme quantile highlight the importance of studying the behavior of DEX–CEX tokens in a variety of market circumstances.

Our findings have a number of ramifications for investors, policymakers and portfolio managers. It is crucial for investors to keep an eye on the DEX–CEX tokens trading activity. Despite making up a relatively minor share of the overall financial markets, the DEX–CEX tokens have a significant impact on the interconnectedness of the various financial assets, particularly in the event of a rapid upward market surge. Our research suggests that, during turbulent times like COVID-19, there is a greater degree of interconnectedness between DEX–CEX tokens and other assets. It also suggests that, during the period of market short squeeze, the DEX–CEX tokens may have contagious effects on other assets, which would reduce the efficacy of portfolio management strategies and risk mitigation. Furthermore, according to our findings, DEX–CEX tokens are the best option for hedging Oil, whilst DEX and CEX tokens offer the fewest hedging possibilities for investors of Gold and the USD dollar index. Our analysis is limited to the return connectedness of DEX–CEX exchange tokens with other assets. Future research may broaden this line of inquiry by comparing and incorporating several classes of digital tokens, such as Utility tokens, Security tokens, Payment tokens, Non-fungible tokens, Decentralized Finance tokens, and Assets-backed tokens to better understand both positive and negative contagion effects of these volatile markets.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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