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Extreme spillovers between insurance tokens and insurance stocks: Evidence from the quantile connectedness approach☆

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ABSTRACT

This study examines potential tail spillovers between insurance tokens and conventional stocks using the quantile connectedness approach by Ando et al. (2022). In particular, this study explores static and dynamic spillovers at lower and upper tails of the return distribution. In line with previous studies, tokens and conventional stocks within the insurance market may show positive but low connectedness levels. Furthermore, our findings confirm a higher sensitivity of the insurance system at both tails of the distribution in comparison with the median ($Q = 0.50$). As expected, dynamic connectedness measures change over time, intensifying at the extremes of the distribution. This finding is confirmed by the robustness test that consists of analyzing the RTD (Relative Tail Dependence) measure, as we reject the symmetric response, since its values are clearly different from zero in most of the sample period. These results are of interest to portfolio managers, as the findings will allow them to suggest adjustments to investment portfolios according to the evolution of the dynamic spillovers found.

1. Introduction

Blockchain technology emerged as a response to the deterioration of trust in the traditional financial industry provoked by the 2008 financial crisis. The development of blockchain and other distributed ledger technologies has leaded to the expansion of Decentralized Finance (DeFi) as a new infrastructure of financial services in which the traditional intermediaries are replaced by a blockchain-based network (Popescu, 2020; Van der Merwe, 2021). DeFi users operate on a peer-to-peer basis through distributed trust platforms that enable to process financial transactions and exchange value, by means of lending-borrowing, asset speculation, diversification or insurance, bypassing traditional financial institutions (Chohan, 2021). Moreover, the term DeFi encompasses the protocols, smart contracts, digital assets and decentralized applications that conform this new financial ecosystem in which transactions are efficient, transparent, borderless and accessible (Schär, 2020; Chen and Bellavitis, 2020).

With the technology evolving rapidly, the DeFi sector has undergone a tremendous growth in recent years (Meyer et al., 2022). The consequent proliferation of digital assets has been accompanied of a crescent necessity of protection against new financial risks from the ongoing DeFi users. Thus, according to CipherTrace, in the last months, most illicit activities are shifting from cryptocurrencies to DeFi protocols and during 2021 and the first quarter of 2022, the total value stolen on the top ten DeFi-related cyberattacks was $2.4 billion.[1]

Apart from its role as a major investor in financial markets, the insurance industry is a key element of the global economic system[2] due to its essential function of risk mitigator. Like almost every industry, as blockchain technologies take hold, insurance sector can be expected to experience an important business

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1 The August 2021 Poly Network hack and the March 2022 Ronin Network exploit constituted nearly half of the overall figure according to the Cryptocurrency Crime and Anti-Money Laundering report, June 2022 (www.cyphertrace.com).

2 According to the Insurance Global Market Report 2022 released by the Business Research Company, the global insurance market value is $5.9 trillion and is expected to reach $8,4 trillion in 2026.

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model disruption (Chen and Bellavitis, 2020). Moreover, in this new financial ecosystem, insurance has a crucial role to respond to the emerging of the novel needs of risk cover, such as loss of digital assets, smart contract failures because of bugs or hacks, thefts and frauds. However, traditional insurers are failing to respond to this rising demand[3] and decentralized insurance solutions are emerging as alternatives to the service offered by traditional insurance providers. Decentralized insurance protocols are member-driven, based on pooling insurance premiums on a risk-sharing platform, and use the smart contracts to offer covers without the need for an insurance company. As other Decentralized Autonomous Organizations (DAO), decentralized insurance protocols use membership tokens (Cong et al., 2022) for holding voting rights, for transactions and for incentivizing correct behaviors (Cousaert et al., 2022).

Although currently the token-based insurance solutions market is still immature and mainly dominated by Nexus Mutual,[4] peer-to-peer insurance can bring improvements in different aspects: efficiency gains in terms of cost and time, data transparency, reduction of management cost, automated claim management, broaden access to insurance,[5] or eliminations of common sources of fraud. The increasing importance of blockchain-based insurance solutions makes relevant the understanding of its intersection with the traditional insurance sector. Thus, this paper dives into the interaction between insurance DeFi and traditional assets across market situations, which can have important implications for portfolio managers and regulators.

Although recent researches have analyzed the spillover effects among decentralized and conventional assets (Ghabri et al., 2022; Nguyen et al., 2022; Umar et al., 2022; Kumar et al., 2022; Yousaf et al., 2022a,b,c; Yousaf and Yarovaya, 2022b; Yousaf et al., 2023a,b, among others), the review of the extant literature highlights the absence of studies focused on the tokens issued by insurance protocols on blockchain. As previously stated, the growing relevance of the DeFi insurance sector raises the need of empirically evaluating its interdependence with the conventional insurance assets. Moreover, given that literature has demonstrated that connectedness increases during extreme events (Bouri et al., 2021), this study aims to analyze the extreme spillovers between the insurance tokens and insurance stocks using the QVAR approach of Ando et al. (2022). In particular, we estimate the connectedness at median, extreme lower, and extreme upper quantiles. For robustness of the results of connectedness at median, we also provide the results of mean-based connectedness using the approach of Diebold and Yilmaz (2012).

The contribution of this paper is threefold. First, we extent the scarce literature on spillovers between Defi tokens and traditional assets. Second, we fill a research gap by focusing on insurance digital assets. To the best of our knowledge, this is the first study to provide insights into the interdependencies between insurance tokens and conventional insurance stocks. Furthermore, we select the top two tokens and the top eight stocks based on the market cap for the analysis period (21 July 2020 to 18 October 2022) to ensure the representativeness of both markets. Finally, the extreme quantile-based approach implemented in the study allows us to compare the behavior of the tails of the return distribution associated with bullish and bearish market conditions.

[3] B3i (the Blockchain Insurance Industry Initiative) filed for insolvency last July after failing to raise new capital. This company was designed as a collaboration between various insurers to explore the potential of blockchain within the insurance industry (Insurance Journal, 2022) https://www.insurancejournal.com/news/international/2022/07/29/677926.htm.

[4] The protocol Nexus Mutual currently has around 150 mill USD in cover (December 27, 2022), but at its peak in 2021 had over 1 billion USD in cover.

[5] As pointed out by the Geneva Association (2019), the underinsurance is not limited to emerging countries but is also present in advanced economies.

Main findings reveal that there would be positive low interdependences between insurance tokens and conventional stocks, by showing a higher sensitivity at both tails of the distribution ($Q = 0.05$ and $Q = 0.95$). These results are in line with previous studies regarding other ERC-20 tokens, such as Long et al. (2022), Yousaf et al. (2022a,c), and provide evidence that digital insurance tokens constitute a new insurance asset class.

In addition, several time-varying connectedness measures explored in this study change over time, reaching peaks at the extremes of the distribution, which is corroborated by the RTD (Relative Tail Dependence) measure, because its values are undoubtedly different from zero during the sample period. Portfolio managers would be interested in these results since they will be able to adjust investment portfolios based on how dynamic spillover changes over time.

The remainder of the paper is structured as follows: Section 2 reviews the extant literature. Section 3 describes the data and methodology used in the study. Results are presented in Section 4 and the conclusions and implications are summarized in Section 5.

2. Literature review

With the proliferation of investment on technology assets, there is a growing interest in understanding and disentangling their drivers. Apart from the abundantly researched conventional cryptocurrencies, one group of DeFi tokens that have attracted the attention of researchers are stablecoins, either analyzing their stability in comparison with cryptocurrencies (Grobys et al., 2021; Hoang and Baur, 2021) or the impact of their issuance on cryptocurrency markets (Ante et al., 2021a,b; Grobys and Huynh, 2021; Kristoufek, 2021) or their role as a safe haven for traditional cryptocurrencies (Baur and Hoang, 2021; Wang et al., 2020; Wasiuzzaman and Haji Abdul Rahman, 2021).

More recent studies have studied the linkages between stablecoins and traditional assets (Smales, 2021; Ghabri et al., 2022; Nguyen et al., 2022; Kumar et al., 2022). In concrete, Smales (2021) employs a dynamic conditional correlation-MGARCH model to study the return and volatility interconnectedness of three cryptocurrencies, Bitcoin, Ether and Tether, finding unidirectional spillovers from Bitcoin and Ether to Tether and from Bitcoin to Ether in the short term and a bidirectional long-term relation of Bitcoin and Ether. Ghabri et al. (2022) apply effective transfer entropy to study the causality network between crude oil, Bitcoin and various stablecoins. Their results show changes in the direction of causal relations among them after the COVID-19 crisis. Particularly, they find that stablecoins become leaders of crude oil prices, whereas the Bitcoin becomes a follower of WTI. On another hand, employing GARCH, EGARCH and fixed effects models, Nguyen et al. (2022) analyze the effect of changes in the US federal funds rate and the Chinese interbank rate on stablecoins and traditional cryptocurrencies. They find that higher rates impact negatively the prices and price volatility of the former while lead to higher prices and volatility of cryptocurrencies. Finally, Kumar et al. (2022) analyze the return and volatility connectedness among ten leading cryptocurrencies and find that both increase significantly, especially in the short horizon, coinciding with the COVID-19 outbreak period and the monetary injections that occurred in reaction to the induced economic crisis. Their results show that cryptocurrency markets are sensitive to shocks related to the global economy, as other financial assets.

As argued by Yousaf and Yarovaya (2022b) a deeper understanding of the nexus between digital and traditional financial assets is still needed to determine the diversifying or even hedging nature of digital assets. In particular, the branch of literature focused on the linkages between Ethereum DeFi ERC-20 tokens and other asset classes is still meager. Indeed, the scarce literature on this area is limited to Kumar et al. (2022), Corbet et al. (2022), Karim et al. (2022), Umar et al. (2022), Yousaf et al. (2022a,b,c), Yousaf and Yarovaya (2022b) and Yousaf et al. (2023a,b). Kumar et al. (2022) investigate the connectedness of the three major cryptocurrencies (Bitcoin, Ethereum and XRP) with other asset classes, namely US stock indices, gold and crude oil. Their results suggest an increase in the connectedness among the different markets during the pandemic period. Using Granger causality, Corbet et al. (2022) assess the determinants of Defi tokens (represented by an index consisting of the five tokens with the highest market capitalization) by examining their linkages with cryptocurrencies (Bitcoin), Defi platforms (Ethereum) and investor attention (Google Trend). The two first are found to influence DeFi prices only during downward market conditions whereas investor attention drives token prices across both positive and negative market conditions.

Yousaf et al. (2022b) analyze the dependence structure between DeFi assets and major currencies returns. Their results indicate low connection between both markets at the static level, while demonstrate a rapid increase in connectedness coinciding with the outbreak of the pandemic in March 2020. In the same vein, Yousaf et al. (2022c) examine the static and dynamic return connectedness between renewable energy tokens and fossil fuel markets (WTI oil, Brent oil and Natural gas). By employing a quantile-based regression approach, their outcomes reveal an increase of the spillovers between the performances of the digital and traditional energy assets under extreme market conditions. Net connectedness analysis shows that, whereas under normal market conditions the WTI oil behaves as a net transmitter of returns spillovers to the renewable digital assets, during bearish and bullish market conditions that role is played by Brent oil and natural gas, respectively. The dynamic analysis shows a time-varying asymmetric return connectedness an upsurge of dependence during the COVID-19 pandemic. Furthermore, Yousaf et al. (2023b) explore the quantile connectedness between meme tokens, meme stocks, and other conventional assets such as S&P500, gold, oil, Bitcoin, U.S dollar and U.S. Treasuries, demonstrating asymmetric behavior of the spillovers between them. In particular, the magnitude of the connectedness between meme assets and other asset classes is stronger in bullish markets.

By using the TVP-VAR framework, Yousaf and Yarovaya (2022b) examine the return and volatility spillovers between new digital assets (DeFis and NFTs) and selected traditional assets (equities and commodities such as gold and oil and traditional cryptocurrencies). They demonstrate weak static dependence between both classes of markets and highlight the potential diversification benefits of adding digital assets in portfolio management strategies. On the basis of the same approach, Umar et al. (2022) analyze the connectedness between DeFi tokens, NFTs, and traditional financial assets, finding significant changes in return and volatility due to the COVID-19 pandemic. Karim et al. (2022) extend Diebold and Yilmaz's approach to the extreme quantiles and examine the transmission of risk among DeFi Tokens, NFTs and traditional cryptocurrencies in extreme quantiles. They identify NFTs as the less interrelated within blockchain markets, leading them to conclude that are the assets with the highest potential for diversification.

In terms of the methodology, Iqbal et al. (2022a) and Iqbal et al. (2022b) use a quantile-based approach to analyze volatility spillovers across different financial markets. They highlight the importance of understanding volatility spillovers for risk management and financial stability, especially during crisis periods. Despite using different sample periods and datasets, both studies include several markets and asset classes, and the results show that the identity of transmitters and receivers of volatility shocks differs between normal and high volatility conditions. The papers suggest that the findings have implications for investors, policymakers, and risk managers concerned with the stability of commodity and equity markets.

Using the quantile-connectedness technique, Yousaf et al. (2022a) analyze the extreme connectedness between digital lending tokens and traditional commercial banks finding positive but low connection between them with connectedness being higher under extreme conditions, especially in downward markets. Finally, Yousaf et al. (2023a) explore the connectedness between three DeFi assets and eleven sector stock indices. In addition, it finds positive but low intensity interdependencies between digital and conventional assets, which intensify in the tails of the distribution. In line with other papers, sensitivity is particularly relevant in the left tail, associated with periods of economic turbulence, such as the COVID-19 crisis. These results are of relevance for market participants in general and, in particular, for portfolio managers.

To further explore the potential diversification role that digital assets could play when included in investment portfolios with other conventional financial assets, our paper extends this line of research by focusing on the insurance sector. In particular, the above literature review reveals a lack of empirical evidence on the spillovers between insurance DeFis and traditional insurance stocks. Our research contributes to literature by uncovering static and dynamic extreme connectedness within this extended insurance system.

3. Method and data

3.1. Data

In line with previous studies such as Mensi et al. (2022) and Yousaf et al. (2022c) among others, this study explores several pairs of insurance tokens and some insurance stocks. In concrete, we utilize the daily data of two insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price)[6] and eight insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI-Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited). We chose the highly capitalized insurance tokens based on their availability of data, whereas the insurance stocks are in the top eight highly capitalized stocks in the world. We extract the data of insurance tokens from the website of coinmarketcap.com and the data of insurance stocks are taken from the website of investing.com. We use the data of insurance tokens and insurance stocks from 21 July 2020 to 18 October 2022.[7]

Fig. 1 describes the dynamics of the top two insurance tokens (NXM and SURE) and the leading eight insurance stocks all over the world (UNH, ELV, AIA, PAI, CLIC, CGC, MMC, and CB). On one hand, some insurance stocks exhibit an upward trend throughout the sampling period, such as UNH, ELV, CGC, MMC and CB, whereas PAI, CLIC, and, to a certain extent, AIA, show a dropping path for much of the sample period. On the other hand, the two leading insurance tokens show several rises and falls, so this could indicate the existence of potential connectedness at tails of the distribution. Moreover, according to Yousaf

[6] InSure DeFi is the world-first DeFi, NFT, Metaverse Insurance Ecosystem with Staking Power. For more details: https://insuretoken.net/. Nexus Mutual is the insurance alternative for crypto and other components of the crypto ecosystem. For further details: https://nexusmutual.io/.

[7] The beginning of the period coincides with the date in which NXM started to trade.

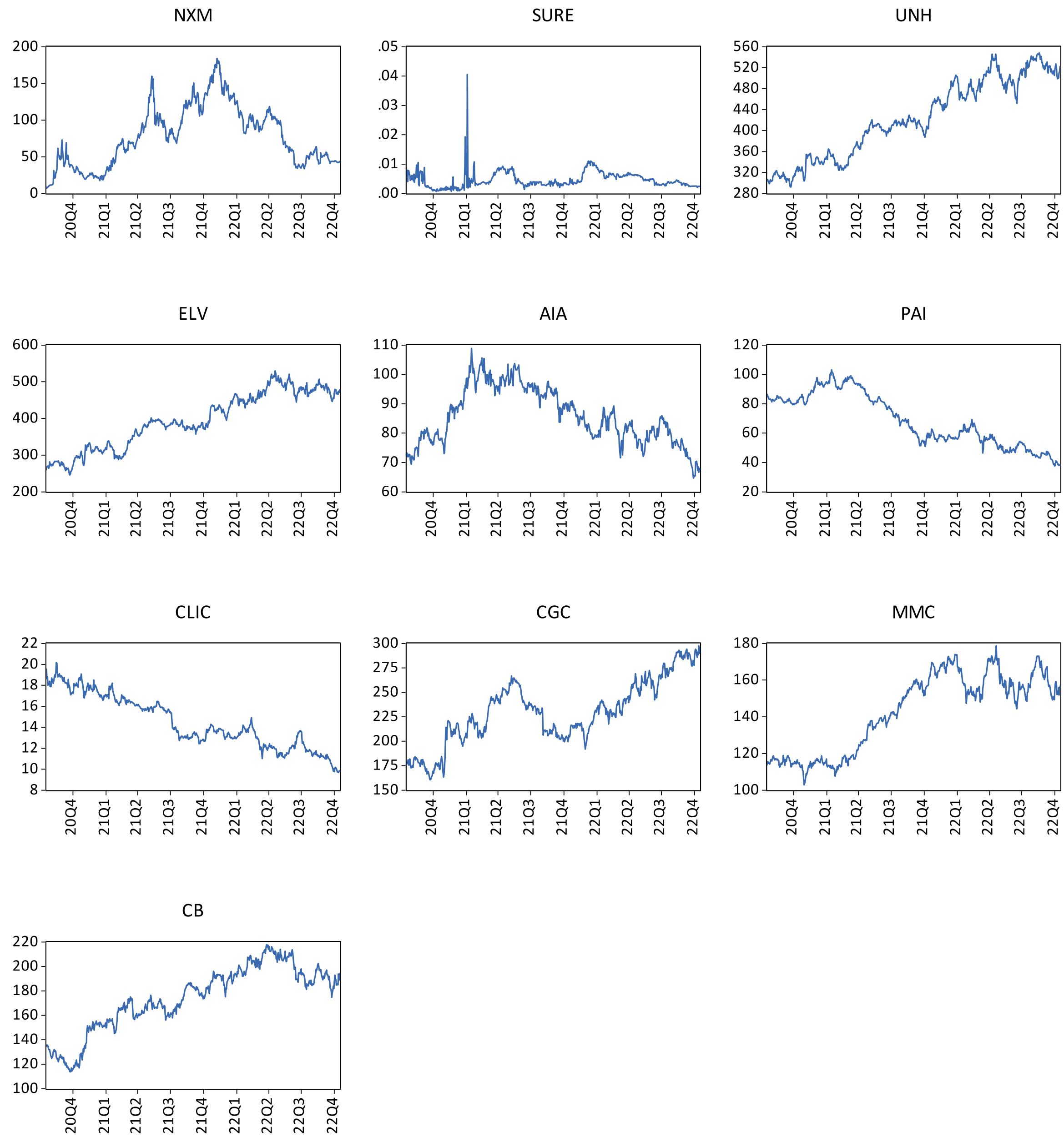

Fig. 1. Prices of Insurance tokens and stocks.
Notes: This figure plots daily prices of two insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and eight insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) from 21 July 2020 to 18 October 2022.

et al. (2022c) and Yousaf and Yarovaya (2022a,b), among others, during the first quarter of 2021 a bubble episode occurs in the cryptocurrency market, which is observed in the large price rise experienced by SURE. Thus, in line with Bouri et al. (2021) and Yousaf et al. (2022a,b), among others, this finding may suggest the study of possible spillovers at different quantiles. In addition, Fig. 2 illustrates the time evolution of daily log returns, showing seemingly stationary series, as expected.

Furthermore, Table 1 presents the descriptive statistics for log returns of the leading two insurance tokens and eight insurance stocks. The mean return is positive in all cases except for PAI and CLIC, remarking that the mean return of the two insurance tokens is slightly higher than that of all insurance stocks. In line with previous studies, such as Yousaf et al. (2022c), digital assets are more volatile as compared to the conventional insurance stocks, with SURE being the most volatile token. All tokens and stocks are positively skewed (except for MMC), and leptokurtic, showing excess kurtosis (Long et al., 2022; Yousaf et al., 2022c). According to the Jarque–Bera test, the null hypothesis of a normal distribution is strongly rejected for all variables. According to Bouri et al. (2021) and Yousaf et al. (2022a), these findings would indicate that extreme positive and negative spillovers should be studied, and any evidence of asymmetry should be addressed. Furthermore, the result of the ADF unit root test shows that all insurance tokens and stocks are stationary, and the null hypothesis of unit root is rejected at 1% significance level. Moreover, according to Jena et al. (2022) and Yousaf et al. (2022a), due to the leptokurtic nature of all data series, the Zivot and Andrews

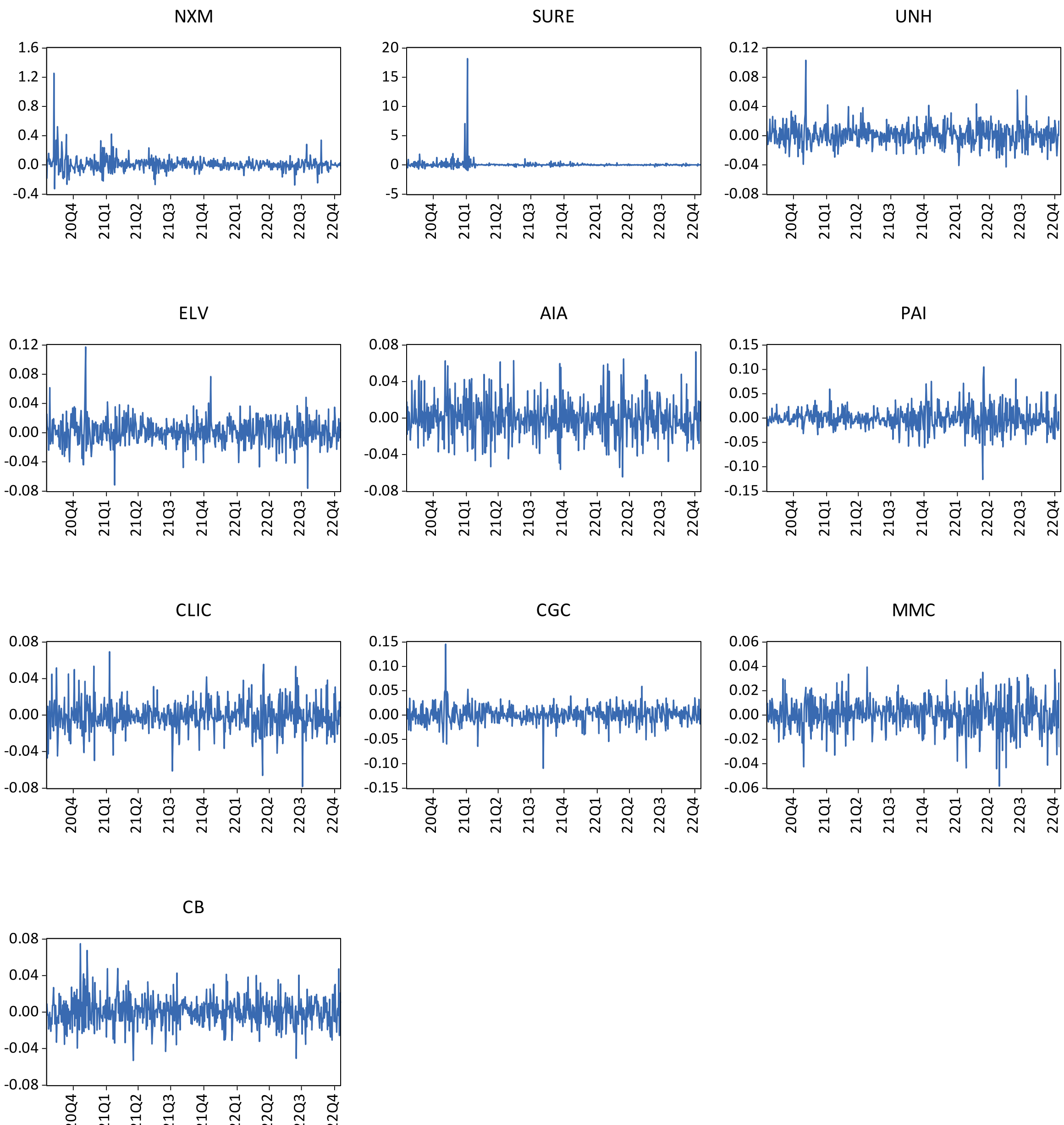

Fig. 2. Returns of Insurance tokens and stocks.
Notes: This figure shows daily log-returns of two insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and eight insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) from 21 July 2020 to 18 October 2022.

(1992) unit root test has been applied, corroborating the previous findings in most of the series.

Table 2 shows the bivariate unconditional correlations between the top two insurance tokens, and the top eight insurance stocks. In general, the two insurance tokens are positively correlated with the insurance stocks, except for SURE-AIA and SURE-MMC, reaching values below 10% in most cases. Furthermore, all insurance stocks are positively correlated, with values below 10% in some cases, but above 50% in some others, such as ELV-UNH, CGC-UNH, MMC-UNH, CGC-ELV, PAI-AIA, CLIC-AIA, and CLIC-PAI. In line with Yousaf et al. (2022a), the leading insurance tokens may show low positive correlations, being even negative in some cases, by suggesting potential roles as a diversifier or hedger when constructing investment portfolios. However, according to Jena et al. (2022) and Yousaf et al. (2022a), among others, this bivariate correlation measure may not be reliable for various reasons, including its linearity, the impact of possible omitted variables, its static structure, as well as the effect of possible changes in market conditions. For all these reasons, in this paper we apply a nonlinear and asymmetric dynamic framework to explore the connectedness level between insurance tokens and stocks, which considers the high cross-correlations resulting from common shock transmitters. Thus, the application of this methodology is presented as critical in examining the potential diversifying role of new digital insurance assets.

3.2. Methodology

Following Ando et al. (2022), we employ the quantile connectedness approach to examine the quantile transmission mechanism among insurance tokens and insurance stocks. This methodology is applied in recent studies such as Bouri et al. (2020, 2021), Liu et al. (2021), Billah et al. (2022), Iqbal et al. (2022a,b), Jena et al. (2022), Long et al. (2022), Mensi et al. (2022), Pham

Table 1
Summary statistics.

	Mean	Max	Min	S. Dev.	Skew	Kurt	J. B	ADF	ZA
NXM	0.0069	1.253	−0.325	0.099	4.057	48.914	51359.960[a]	−6.415[a]	−25.65[b]
SURE	0.0731	18.176	−0.953	0.866	17.119	344.998	2790941.0[a]	−7.368[a]	−8.04[a]
UNH	0.0011	0.103	−0.042	0.014	0.791	8.080	668.932[a]	−23.503[a]	−23.54
ELV	0.0012	0.117	−0.076	0.017	0.387	7.506	493.822[a]	−23.846[a]	−23.89[b]
AIA	0.0001	0.072	−0.064	0.020	0.354	4.066	38.768[a]	−26.691[a]	−17.04[b]
PAI	−0.0012	0.104	−0.126	0.022	0.192	6.353	269.073[a]	−25.225[a]	−12.34[a]
CLIC	−0.0011	0.069	−0.078	0.016	0.081	5.642	165.519[a]	−25.119[a]	−11.79[c]
CGC	0.0011	0.145	−0.109	0.018	0.349	11.824	1850.872[a]	−23.364[a]	−23.49[b]
MMC	0.0007	0.039	−0.058	0.013	−0.368	4.432	61.280[a]	−23.324[a]	−23.46[c]
CB	0.0008	0.074	−0.052	0.015	0.314	4.587	68.881[a]	−25.034[a]	−25.08

Notes: This table collects some relevant descriptive statistics of log-returns of two insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and eight insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) from 21 July 2020 to 18 October 2022. In concrete: Max—Maximum, Min—Minimum, S.Dev.—Standard deviation, Skew—Skewness, Kurt—Kurtosis, J.B—Jarque Berra test, ADF—Augmented Dicky Fuller test, (Zivot and Andrews, 1992) sequential test for a unit root-ZA.
[a]Significance at the 1% level.
[b]Significance at the 5% level.
[c]Significance at the 10% level.

Table 2
Unconditional correlations.

	NXM	SURE	UNH	ELV	AIA	PAI	CLIC	CGC	MMC	CB
NXM	1.000									
SURE	0.075	1.000								
UNH	0.110	0.101	1.000							
ELV	0.069	0.065	0.813	1.000						
AIA	0.024	−0.051	0.042	0.054	1.000					
PAI	0.019	0.008	0.034	0.066	0.561	1.000				
CLIC	0.022	0.042	0.059	0.059	0.565	0.744	1.000			
CGC	0.086	0.052	0.681	0.713	0.084	0.077	0.106	1.000		
MMC	0.139	−0.007	0.512	0.448	0.048	0.090	0.075	0.397	1.000	
CB	0.072	0.106	0.343	0.366	0.083	0.081	0.074	0.391	0.473	1.000

Notes: This table shows unconditional correlations between several pairs of insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) from 21 July 2020 to 18 October 2022.

and Cepni (2022), Yousaf et al. (2022a,c), Yousaf and Yarovaya (2022c), Yousaf et al. (2023a,b) and Aharon et al. (2023), among others. To accurately compute the quantile connectedness metrics, we define an infinite order vector moving average (MA) representation of a quantile vector auto regression QVAR(p), as follows:

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

Following Koop et al. (1996) and Pesaran and Shin (1998), the generalized forecast error variance decomposition (GFEVD) with a forecast horizon H is specified as:

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

where e_i represents a zero vector with unity on the ith position. The normalization of each element in the decomposition matrix is:

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

Following Diebold and Yilmaz (2012), Diebold and Yilmaz (2014), the connectedness measures based on GFEVD are expressed as:

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

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

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

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

$TO_{j,t}$ represents the aggregated impact of a shock in variable j has on all other variables whereas $FROM_{j,t}$ illustrates the aggregated influence of all other variable have on variable j. $NET_{j,t}$ indicates the difference between "TO" and "FROM", where a positive value means a net transmitter and a negative value refers to a net recipient from the other markets, respectively. TCI_t represents the average level of total connectedness.

4. Empirical results

In line with Bouri et al. (2021), Liu et al. (2021), Jena et al. (2022), Billah et al. (2022), Jena et al. (2022), Long et al. (2022), Mensi et al. (2022), Pahm and Cepni (2022), Yousaf et al. (2022a,c), Yousaf and Yarovaya (2022c), Yousaf et al. (2023a,b) and Aharon et al. (2023), among other recent studies, our research applies the quantile VAR model to estimate the potential tail connectedness between the returns of the top insurance tokens and stocks included in this study.[8] Furthermore, for robustness, the results of the conditional median spillover are compared to the results

[8] In line with Yousaf et al. (2022a), among others, this study is based on the Akaike information criterion (AIC), and a rolling-window approach using 100 days.

Table 3
Static return spillovers at median ($Q = 0.50$).

	NXM	SURE	UNH	ELV	AIA	PAI	CLIC	CGC	MMC	CB	FROM
NXM	68.09	6.16	3.31	2.82	2.87	2.37	2.67	2.75	5.51	3.45	31.91
SURE	7.88	79.56	2.07	1.48	2.15	1.38	1.73	1.15	1.08	1.51	20.44
UNH	2.08	1.41	39.01	23.88	0.94	0.96	0.77	16.48	8.64	5.82	60.99
ELV	1.61	1.18	23.91	38.90	0.75	0.94	0.79	18.56	7.05	6.31	61.10
AIA	1.59	1.47	1.95	2.41	55.89	14.77	15.00	1.43	3.37	2.12	44.11
PAI	1.05	1.08	1.71	1.91	12.99	48.31	24.66	2.77	3.06	2.47	51.69
CLIC	1.33	0.80	1.66	1.80	12.85	24.60	48.51	2.88	3.47	2.10	51.49
CGC	1.59	1.46	17.31	19.61	0.81	0.73	1.27	42.96	6.82	7.43	57.04
MMC	3.17	1.24	11.03	9.32	1.50	1.79	1.92	7.63	50.52	11.88	49.48
CB	1.78	1.22	7.32	8.47	1.48	1.74	2.87	9.14	12.03	53.97	46.03
TO	22.08	16.01	70.26	71.70	36.36	49.28	51.68	62.79	51.02	43.11	474.28
Inc.Own	90.17	95.58	109.28	110.60	92.24	97.59	100.19	105.75	101.54	97.07	TCI
NET	−9.83	−4.42	9.28	10.60	−7.76	−2.41	0.19	5.75	1.54	−2.93	47.43

Notes: This table collects the static return spillovers at median between insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH–UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) during the sample period between 21 July 2020 and 18 October 2022.

Table 4
Static return spillovers at extreme lower quantile ($Q = 0.05$).

	NXM	SURE	UNH	ELV	AIA	PAI	CLIC	CGC	MMC	CB	FROM
NXM	15.93	7.98	9.74	9.95	9.03	9.02	8.68	9.60	9.77	10.30	84.07
SURE	9.38	23.10	9.09	8.89	7.91	8.21	8.09	8.29	8.13	8.91	76.90
UNH	8.34	6.88	14.93	12.70	7.64	9.09	8.04	11.14	10.88	10.38	85.07
ELV	8.25	6.48	12.58	15.29	8.61	8.64	8.03	11.34	10.44	10.35	84.71
AIA	8.68	7.06	9.02	9.54	15.48	11.25	10.79	8.94	9.32	9.92	84.52
PAI	7.89	6.61	9.51	9.65	10.50	15.59	11.54	9.02	9.86	9.84	84.41
CLIC	8.63	7.19	8.97	9.48	10.52	11.64	14.39	9.38	9.84	9.95	85.61
CGC	8.39	7.12	11.65	11.75	8.28	8.53	8.19	15.29	10.04	10.77	84.71
MMC	8.36	6.96	10.86	10.59	8.39	9.57	8.73	9.99	15.02	11.54	84.98
CB	9.19	6.90	9.91	10.30	8.54	9.02	8.67	10.09	11.16	16.21	83.79
TO	77.11	63.20	91.33	92.84	79.41	84.95	80.76	87.79	89.42	91.95	838.77
Inc.Own	93.04	86.30	106.25	108.13	94.90	100.54	95.15	103.07	104.44	108.16	TCI
NET	−6.96	−13.70	6.25	8.13	−5.10	0.54	−4.85	3.07	4.44	8.16	83.88

Notes: This table collects the static return spillovers at extreme lower quantile between insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) during the sample period between 21 July 2020 and 18 October 2022.

from the Diebold and Yilmaz (2012) conditional mean spillover. Moreover, further analyses on the difference between the tail dependence in the upper and lower quantile, that is, the relative tail dependence (RTD), as well as a time-varying return spillover study are conducted.

4.1. Static quantile spillover analysis

This research estimates some static quantile connectedness measures between top insurance tokens and conventional stocks. In concrete, Table 3 collects the median ($Q = 0.5$), and Tables 4 and 5 the lower and upper tails of the return distribution ($Q = 0.05$ and $Q = 0.95$, respectively).

Regarding the conditional median spillovers, insurance tokens (NXM and SURE) exhibit the smallest spillovers from the return on other assets, due to their higher proportion of self-explained return (68.09 and 79.56, respectively). In addition, in line with previous studies, such as Yousaf et al. (2022a), NXM and SURE also have the smallest connectedness to other insurance assets (22.08 and 16.01, respectively). Among the conventional insurance assets, AIA and CB show the highest self-explained return and the subsequent lowest spillover to other insurance securities. Contrarily, UNH and ELV appear as the most relevant transmitters and receivers in this system. In line with Baur and Hoang (2021) and Yousaf et al. (2022a), the insurance tokens may act as good diversifiers for conventional insurance stocks. In addition, about the net return connectedness, the top two insurance tokens exhibit negative values, which means that they are receivers from the system, as well as for the insurance stocks AIA, PAI, and CB. The rest of the conventional insurance stocks would appear as net transmitters to the system. Finally, in line with studies such as Ji et al. (2019), Bouri et al. (2021), Liu et al. (2021), Yousaf et al. (2022a), among others, the total spillover index between insurance tokens and conventional stocks is about 48%, very similar to that obtained with the conditional mean (Diebold and Yilmaz, 2012) connectedness (please, see Table A.1 in the Appendix). In line with Baur and Lucey (2010), Baur and Hoang (2021), and Yousaf et al. (2022a), among others, the noticeable divergences between insurance tokens and conventional stocks would recommend using either one as a diversifier for the other. Thus, investors may benefit from diversifying their portfolios by investing in both types of assets, and, even, identifying undervalued assets in these markets (Su, 2020). In addition, if insurance tokens and conventional stocks offer different types of risk exposure, investors could use this information to develop more effective risk management strategies that better reflect their risk preferences and investment objectives. Moreover, this finding would suggest that insurance tokens represent a new type of financial asset that may offer unique risk-return characteristics not found in traditional stocks. This could spur innovation in the financial industry and lead to the development of new investment products that incorporate insurance tokens.

As argued above, preliminary analysis of the data suggests examining potential interdependences between insurance tokens and conventional stocks at the upper and lower ends of the return distribution. According to very recent studies such as Bouri et al. (2020), Liu et al. (2021), Billah et al. (2022), Jena et al. (2022), Long et al. (2022), Mensi et al. (2022), Pham and Cepni (2022), Yousaf et al. (2022a), and Aharon et al. (2023), among others, we expect to find differences between measures of conditional mean

Table 5
Static return spillovers at extreme upper quantile (Q=0.95).

	NXM	SURE	UNH	ELV	AIA	PAI	CLIC	CGC	MMC	CB	FROM
NXM	15.68	9.74	10.16	9.39	10.81	8.95	8.46	9.64	8.05	9.14	84.32
SURE	12.35	12.98	10.36	9.19	11.21	9.29	9.12	9.28	7.57	8.64	87.02
UNH	10.19	8.38	13.83	11.07	10.35	9.02	8.28	10.57	8.84	9.46	86.17
ELV	10.06	8.45	11.79	13.07	9.82	9.14	8.32	10.73	9.04	9.58	86.93
AIA	11.62	8.84	10.46	9.39	14.74	9.86	9.18	9.20	7.90	8.82	85.26
PAI	10.49	8.29	9.98	9.43	12.04	12.61	10.98	9.29	7.73	9.15	87.39
CLIC	10.26	8.11	10.18	9.57	11.87	11.39	12.37	9.61	7.83	8.80	87.63
CGC	10.36	8.09	11.18	11.13	9.60	8.84	8.53	13.90	8.66	9.71	86.10
MMC	10.97	8.48	11.36	10.22	10.18	8.96	8.23	10.32	11.81	9.47	88.19
CB	10.71	8.01	11.10	10.26	9.94	9.21	8.51	10.73	8.80	12.72	87.28
TO	97.00	76.39	96.59	89.65	95.83	84.67	79.62	89.37	74.42	82.77	866.29
Inc.Own	112.67	89.38	110.41	102.71	110.56	97.28	91.99	103.27	86.23	95.49	TCI
NET	12.67	−10.62	10.41	2.71	10.56	−2.72	−8.01	3.27	−13.77	−4.51	86.63

Notes: This table collects the static return spillovers at extreme upper quantile between insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) during the sample period between 21 July 2020 and 18 October 2022.

(Diebold and Yilmaz, 2012) and median ($Q = 0.50$) connectedness. Thus, estimates at lower ($Q = 0.05$) and upper ($Q = 0.95$) quantiles allow us to differentiate between extreme negative and positive shocks (Tables 4 and 5 respectively).

Our outcomes confirm that the insurance tokens and stocks included in this study interact more to extreme market conditions, such as the COVID-19 pandemic and the Russian invasion of Ukraine, in line with previous studies about different topics, such as Hu (2006), Feng et al. (2018), Sevillano and Jareño (2018), Bouri et al. (2020), Jareño et al. (2022), Liu et al. (2021), Billah et al. (2022), Escribano et al. (2022), Long et al. (2022), Pham and Cepni (2022), Yousaf et al. (2022a,b,c), among others. In particular, we found similar results to the aforementioned studies, as we observed high return connectedness levels at the extremes of the distribution, as opposed to the spillovers shown at the mean and median of the distribution. The results show a connectedness at the extremes that is almost double that of the mean (48.92%) and the median (47.43%), as it is 83.88% at the lower end ($Q = 0.05$) and 86.63% at the upper end ($Q = 0.95$). In addition, the insurance token SURE would appear as net receiver of spillovers, whereas the conventional insurance stock UNH and ELV, would emerge as net transmitters of connectedness, at both tails ($Q = 0.05$ and $Q = 0.95$). In contrast, the insurance token NXM and the rest of the insurance stocks would have different profiles at extreme quantiles.

Regarding the finding about the slightly higher connectedness at the upper tail of the return distribution would be in line with other studies, such as Long et al. (2022), Yousaf et al. (2022a,c), and Yousaf and Yarovaya (2022c), but contrary to others (Billah et al., 2022; Mensi et al., 2022), which find higher connectedness at the lower end. Consequently, the fact that insurance token-stock pairs are more connected at extreme quantiles, particularly in the lower tail, such as the global pandemic and the war in Ukraine would suggest that the diversifying role of insurance tokens would occur mainly in normal market conditions, but less so in economic booms and mainly in times of economic uncertainty.

Thus, our findings suggest that in extreme market conditions, investors may need to reassess their risk management strategies to account for the increased interaction between insurance tokens and conventional stocks. This could involve adjusting portfolio allocations or hedging strategies. In addition, the increased interaction between insurance tokens and conventional stocks during extreme market conditions could contribute to greater market volatility. This could have implications for investor sentiment, liquidity, and overall market stability (Su, 2020). On the other hand, if the interaction between insurance tokens and conventional stocks is significant during extreme market conditions, it could lead to contagion and amplification of risks across markets and financial institutions. This scenario even could create investment opportunities for investors who can identify undervalued assets or take advantage of market dislocations.

Consistently, Fig. 3 collects the total spillover index showing that the connectedness between insurance token and stock markets are greater in crisis periods, in line with Bouri et al. (2021), Liu et al. (2021), Umar et al. (2021a,b,c), Yousaf et al. (2022a). Thus, both extreme positive and negative shocks show increasing conditional return spillovers with shock size (Bouri et al., 2020, 2021; Jena et al., 2022; Yousaf et al., 2022a). In addition, Fig. 3 shows that the total connectedness index for the middle of the distribution ($0.25 < Q < 0.75$) is between 50.00–70.00%. On the other hand, the conditional return connectedness between insurance tokens and conventional stocks exacerbates the risk expansion caused by major shocks. The total spillover index is about 80% at the lowest (5th, 10th) percentiles (related to bear market states) and approaches 90% at the highest (90th, and 95th) percentiles (related to bull market states), showing an approximately symmetric shape. Moreover, for lower ($Q = 0.05$) and upper ($Q = 0.95$) quantiles, in contrast to the conditional mean (Diebold and Yilmaz, 2012) and median ($Q = 0.5$) connectedness measures, the own shock spillover percentages are significantly less than the TCI value, as shown by Jena et al. (2022) and Yousaf et al. (2022a). Thus, if the market moves from a state considered normal to a bullish or bearish state, the connectedness of each security to itself (internal shocks) would be reduced, while the return connectedness from external shocks to the system would increase. Our results could therefore help portfolio managers to guide institutional and individual investors both during bull and bear markets, as our findings suggest that around 85% of the fluctuations in the system are external.

4.2. Dynamic quantile spillover analysis

Following Bouri et al. (2021), Jena et al. (2022) and Yousaf et al. (2022a,b,c), among others, this study explores the time varying total and net quantile connectedness between insurance tokens and conventional stocks. This analysis is necessary due to the changing dynamics of the economic, financial, and geopolitical scenarios that affect the study of the insurance sector, such as the global pandemic and the war in Ukraine, among others.

Fig. 4 plots the time-varying total spillover index in both the middle ($Q = 0.5$) and the ends of the distribution (lower, $Q = 0.05$, and upper, $Q = 0.95$, quantiles), estimated using 100-day rolling estimation windows (Bouri et al., 2021; Jena et al.,

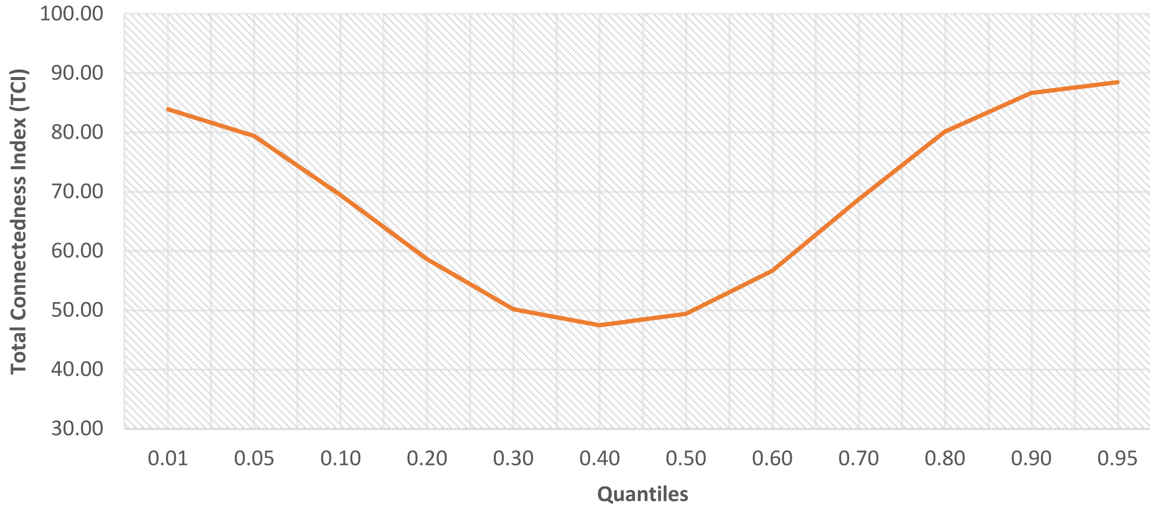

Fig. 3. Variations in total connectedness index (TCI) over various quantiles.
Notes: This figure shows the evolution of the total spillover index between two insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) between 21 July 2020 and 18 October 2022.

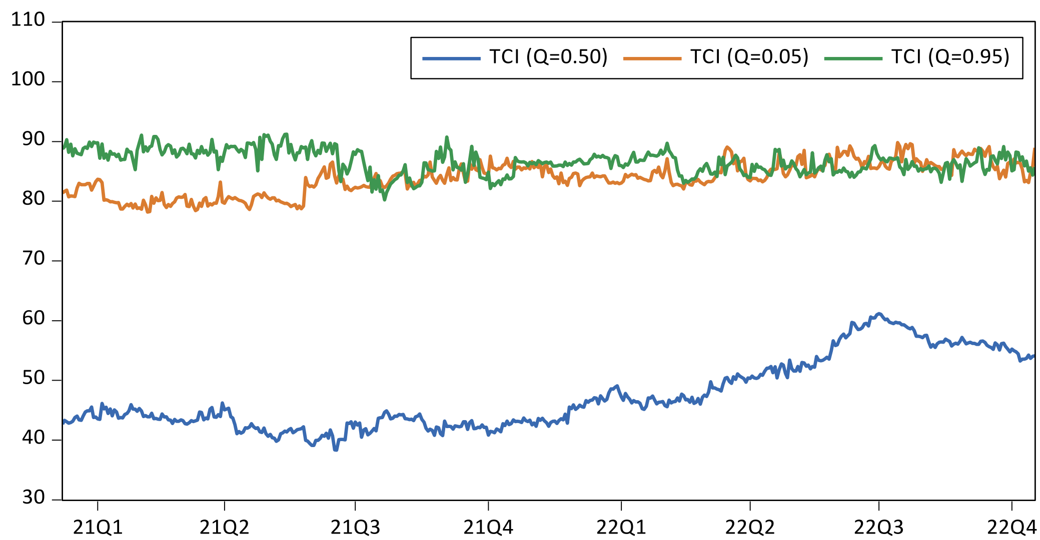

Fig. 4. Time-varying total connectedness index (TCI) at median ($Q = 0.50$), extreme lower ($Q = 0.05$), and upper ($Q = 0.95$) quantiles.
Notes: This figure exhibits the time-varying total spillover index at median, lower and upper quantiles between two insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) between 21 July 2020 and 18 October 2022.

2022; Yousaf et al., 2022a,b,c).[9] First, the time-varying return connectedness changes over time, in line with many previous but recent studies, such as Umar et al. (2021a,b,c), Long et al. (2022), Yousaf et al. (2022a), and Yousaf and Yarovaya (2022c). Second, according to Jena et al. (2022) and Yousaf et al. (2022a) among others, an in-depth analysis of the time-varying return spillovers at different quantiles would be essential to distinguish between positive and negative shocks and could also provide valuable information for portfolio managers. Our findings reveal that the level of the median volatility measures ($Q = 0.5$) is about half that found at the extremes of the distribution ($Q = 0.05$, and $Q = 0.95$). In concrete, the total spillover index at both tails makes higher (80%–90%) than that of the median (40%–50%), suggesting that the leading insurance tokens and the top eight conventional stocks are more sensitive than the median to both extreme positive and negative shocks.

The sample period of this research explores the post-vaccination phase of the COVID-19 global pandemic crisis,[10] and the crisis caused by the war in Ukraine, which has led to a global energy crisis, as well as a significant rise in commodity prices. Thus, within this context, our findings show relevant movements in the time-varying total spillover index. Interestingly, the dynamic total connectedness index is greater in the highest quantile throughout 2021, but in 2022 the total spillover index increases for the lowest quantile to levels like those of the highest

[9] To examine the robustness of the results, we performed sensitivity analyses using 200-day horizons. However, no significant changes were observed in the results.

[10] According to Teherani et al. (2021) and Yousaf et al. (2022a), among others, the first biggest positive news about the effectiveness of vaccine (after trials) appeared on 9th November 2020, because PFIZER and BioNTech announce that the vaccine is 90% effective.

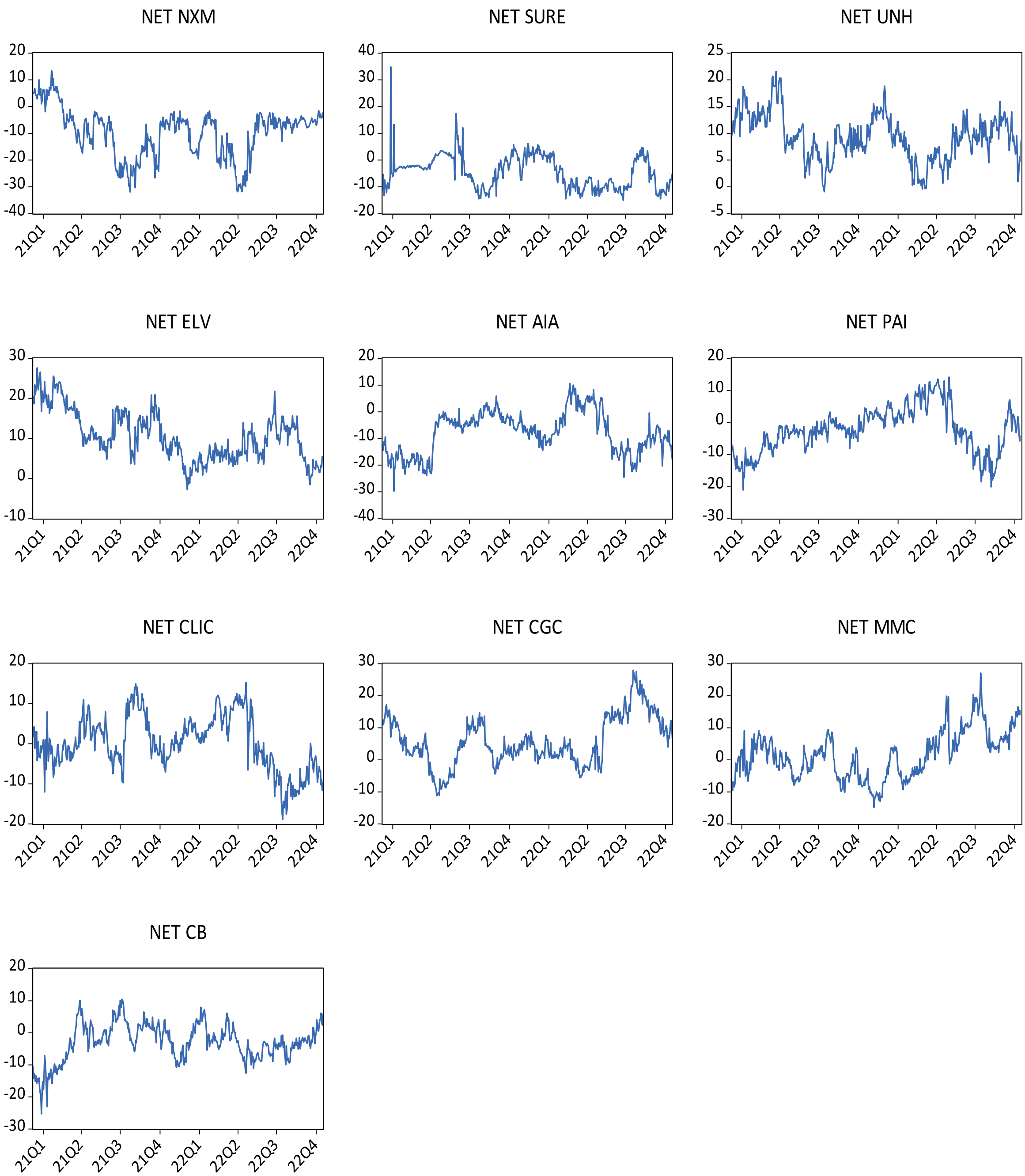

Fig. 5. Time-varying net spillovers at median ($Q = 0.50$).
Notes: This figure shows the time-varying net spillovers at median between two insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) between 21 July 2020 and 18 October 2022.

quantile. Finally, the dynamic total connectedness index for the mid-quantile also rises during 2022, which could be caused by the increased uncertainty caused by the Russian invasion of Ukraine.

Following previous studies (Jena et al., 2022; Yousaf et al., 2022a, 2023a,b), this research explores the time-varying net spillovers at median ($Q = 0.5$), and lower ($Q = 0.05$) and upper ($Q = 0.95$) quantiles, in Figs. 5–7 respectively. Our findings confirm that in all cases that net connectedness measures change over time and does so for each token and stock in the insurance market, as well as for the three quantiles analyzed (median and extremes of the distribution). Moreover, in line with previous studies (Billah et al., 2022; Jena et al., 2022; Long et al., 2022; Mensi et al., 2022; Pham and Cepni, 2022; Yousaf et al., 2022a,c), net spillovers show higher levels of uncertainty in bullish and bearish states of the insurance market, associated with extreme quantiles. This situation could be explained by the external factors affecting the insurance market, which can be of various kinds, such as financial, economic, geopolitical, etc. Again, it is interesting to note that the findings found in the paper could help portfolio managers to adjust their investment positions in extreme market conditions, since, as has been corroborated, the dynamic connectedness changes over time and does so abruptly in bullish and bearish states of the insurance market.

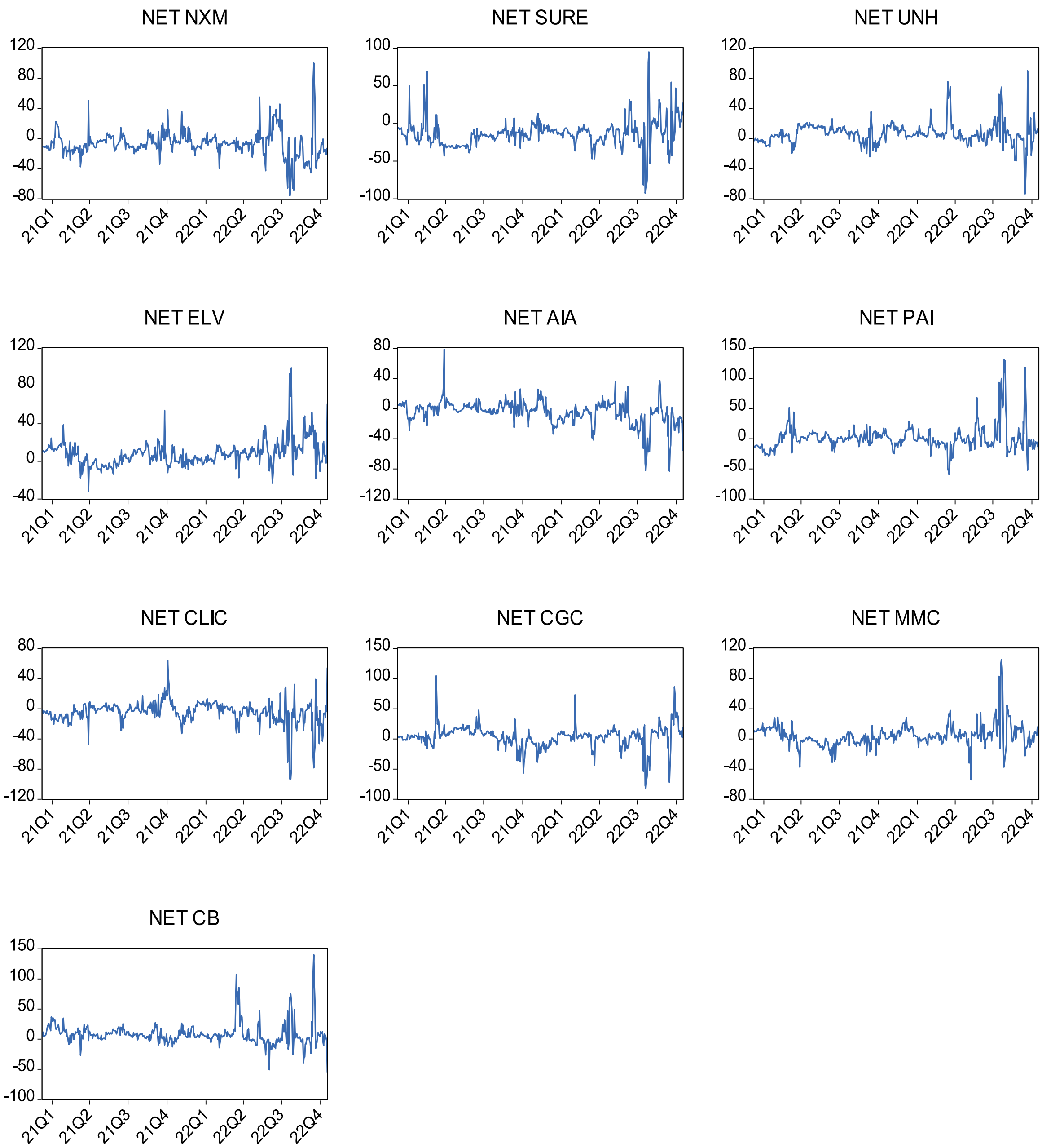

Fig. 6. Time-varying net spillovers at extreme lower quantile ($Q = 0.05$).
Notes: This figure shows the time-varying net spillovers at lower quantile between two insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) between 21 July 2020 and 18 October 2022.

In line with previous findings, these results would suggest that risk management strategies need to be continually reassessed and adjusted over time to reflect changing market conditions. This could include monitoring changes in net connectedness measures and adjusting portfolio allocations or hedging strategies accordingly. In addition, this situation could create investment opportunities for investors who can identify assets that are becoming more or less connected to the broader market. This could allow investors to take advantage of market dislocations or identify undervalued assets. In addition, policymakers may need to consider additional measures to manage risk during periods of increased connectedness (Su, 2020).

4.3. Dynamic net pairwise quantile spillover analysis

In line with Mensi et al. (2022), Long et al. (2022) and Yousaf et al. (2022c), among others, Fig. 8 collects the net pairwise directional connectedness network at different quantiles between insurance tokens and conventional stocks.

The net transmitter or receiver position of each insurance token and conventional stock is represented by the color of each node (green = receiver, blue = transmitter), and the magnitude of the net connectedness is indicated by the size of the node. In addition, the arrow directions of the lines indicate the directions of the net connectedness between the two insurance securities. Thus, consistently with the static connectedness analysis, at the median quantile, both insurance tokens (NMX and SURE), mainly,

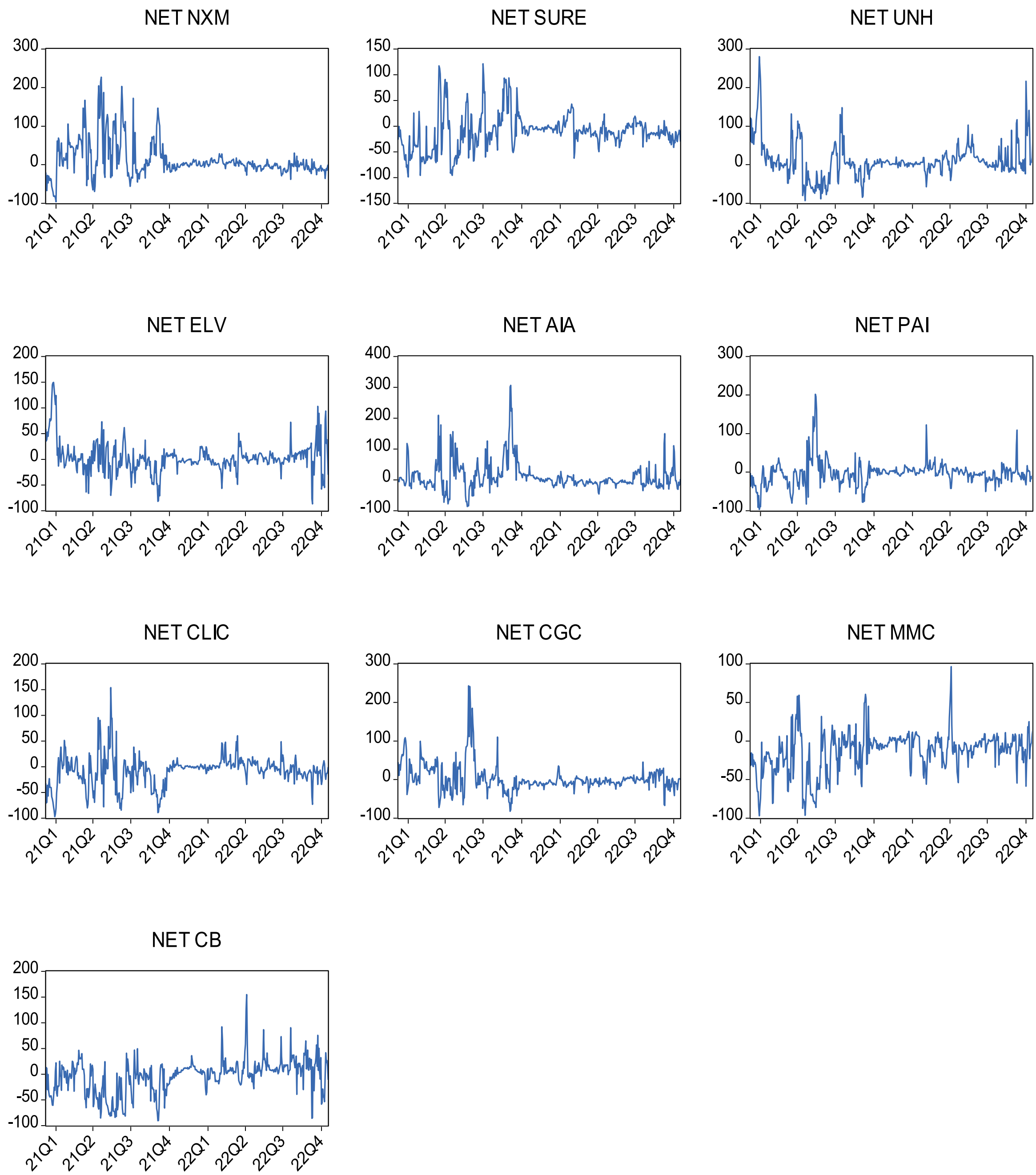

Fig. 7. Time-varying net spillovers at extreme upper quantile ($Q = 0.95$).
Notes: This figure shows the time-varying net spillovers at upper quantile between two insurance tokens (NXM–Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) between 21 July 2020 and 18 October 2022.

and three conventional stocks (AIA, PAI, and CB) may appear as clear risk receivers from the system explored in this research. However, the rest of insurance would seem as risk transmitters, essentially for ELV and UNH. For bearish moments in the insurance market ($Q = 0.05$), the SURE and NXM tokens, along with the conventional stock AIA continue to maintain their net receiver profile, joined by the CLIC asset. The role of the largest net receiver is assumed by the SURE token. Finally, for bullish market states ($Q = 0.95$), the SURE token continues to maintain the same receiver profile, joined by other conventional assets, such as MMC and CLIC, which are larger in size, as well as other assets, whose position is a receiver, but smaller in size (CB and PAI). UNH, NXM and AIA would appear as the larger transmitters of shocks during bullish states of the insurance market. Thus, the alterations we observe in the net position shown by insurance tokens and conventional stocks would be consistent with investors having to actively manage their portfolios by changing the composition of their portfolios in periods of uncertainty (related to distribution tails). Moreover, in line with previous studies, such as Mensi et al. (2022), and Yousaf et al. (2022c), among others, the insurance token–conventional stock system may exhibit asymmetric return spillovers in the tails of the distribution. Therefore, the need for investors to actively manage their portfolios in times of uncertainty could drive financial innovation. Financial instruments

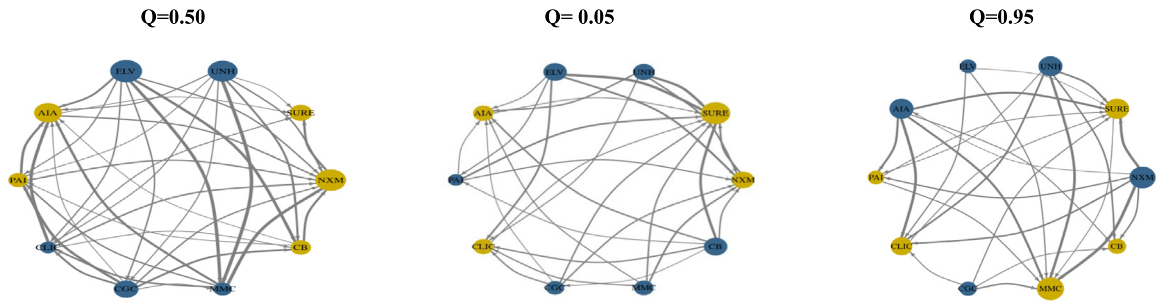

Fig. 8. Net pairwise directional spillover.
Note: The net transmitter or receiver position of each insurance token and conventional stock is represented by the color of each node (green = receiver, blue = transmitter), and the magnitude of the net connectedness is indicated by the size of the node. In addition, the arrow directions of the lines indicate the directions of the net connectedness between the two insurance securities.
The assets under review are two insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) between 21 July 2020 and 18 October 2022.

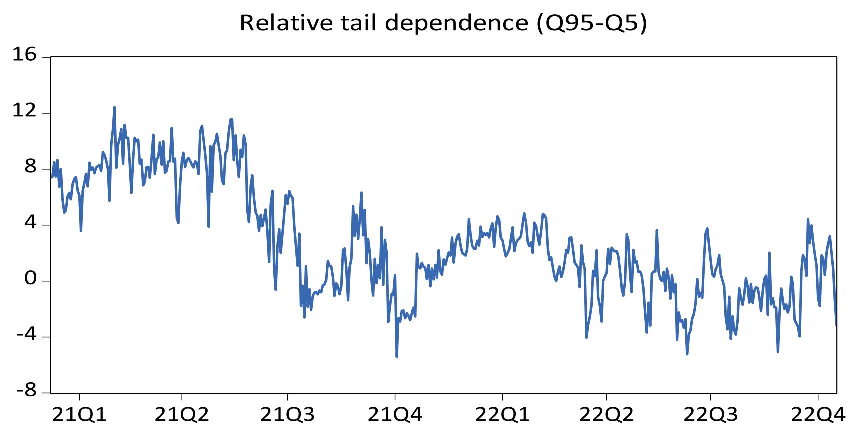

Fig. 9. Relative tail dependence ($TCI_{Q=0.95} - TCI_{Q=0.05}$).
Note: This figure shows the RTD calculated by the difference between the TCI at the 95th quantile and that at the 5th quantile between two insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) between 21 July 2020 and 18 October 2022. The positive and negative value indicates, respectively a strong dependence on the upper and lower quantile.

such as insurance tokens, which offer investors alternative ways to manage risk, may become more popular.

4.4. Relative tail dependence analysis

In the context of the analysis across quantiles, RTD refers to "Relative Tail Dependence" which is a measure of the degree to which two assets are likely to experience large positive or negative returns at the same time, especially during extreme market events. Specifically, RTD measures the proportion of extreme joint observations in the lower or upper tails of the distribution of two assets relative to the proportion that would be expected under the assumption of independence. RTD can be used to complement other measures of connectedness or spillover effects and provide additional insights into the tail risk dependencies between assets (Su, 2020). Thus, based on the evidence shown in the previous section, and following recent papers such as Iqbal et al. (2022a,b), Mensi et al. (2022), Long et al. (2022), Pham and Cepni (2022), Tiwari et al. (2022), and Yousaf et al. (2022a,c), Fig. 9 collects the relative tail dependence (RTD). In concrete, RTD can be defined as the difference between the total connectedness index (TCI) at the extreme upper and lower quantiles ($TCI_{Q=0.95} - TCI_{Q=0.05}$).

According to Long et al. (2022), the nearer the curve is to 0, the more symmetrical the connectedness of left- and right-tails is. In line with Mensi et al. (2022), our findings show great dependence in the lower tail of the distribution during the second half of the sample. This period is featured by the latest waves of the COVID-19 pandemic, the Russian invasion of Ukraine, the energy crisis, as well as the escalation of energy and other commodity prices, and the rise in interest rates by the monetary authorities in Europe and the United States. Thus, in line with previous studies, we confirm the negative impact of such global events on the insurance system explored in this research. Nevertheless, during the first half of the sample, there is evidence of a clear higher dependence in the upper tail of the distribution (Yousaf et al., 2022c). The first part of the sample is a period characterized by the relative control of the COVID-19 pandemic and some economic recovery. Therefore, in line with Long et al. (2022), Yousaf et al. (2022a), among others, our findings evidence asymmetric spillover effects between the extremes of the distribution.

Thus, these findings would have important economic implications for investors, policymakers, and financial institutions as they highlight the need to consider extreme risk spillovers when designing risk management strategies and developing appropriate policy responses to mitigate the negative impact of global events on financial stability (Su, 2020). The results provide important insights into the dynamics of international financial markets and emphasize the need for policymakers and investors to consider the impact of such events when making investment decisions and designing macroeconomic policies.

5. Concluding remarks

Using the quantile connectedness (QVAR) approach of Ando et al. (2022), this study examines potential tail spillovers between top two insurance tokens and leading eight insurance conventional stocks from 21 July 2020 to 18 October 2022. Thus, this study includes a period characterized by several waves of the COVID-19 pandemic, as well as other global events, such as the Russian invasion of Ukraine, the energy crisis, as well as the increase in the price level, mainly of energy and other commodities, and the consequent response of the monetary authorities, increasing the reference interest rates. In addition, there is a particular emphasis in this study on examining static and dynamic spillovers at both the lower and upper tails of the return distribution. Accordingly, we estimate the connectedness at median ($Q = 0.50$), extreme lower ($Q = 0.05$), and extreme upper ($Q = 0.95$) quantiles. For robustness of the results of connectedness at median, we also provide the results of mean-based connectedness using the approach of Diebold and Yilmaz (2012).

Regarding the main findings of this research, first, the insurance market may have positive, but low connectedness levels, in accordance with previous studies. These early results could suggest that leading two insurance tokens could be used as diversifiers or hedging instruments in the management of investment portfolios. Second, our outcomes also reveal higher sensitivity of the insurance system at both tails of the distribution when compared with the median ($Q = 0.50$). Furthermore, in line with expectations, dynamic connectedness measures change over time, increasing at the extremes of the distribution. A robustness test that consists of analyzing RTD (Relative Tail Dependence) confirms this finding, since the values of RTD are clearly different from zero in most of the sampling period. Thus, portfolio managers would be interested in these results, as they will allow them to suggest adjustments to investment portfolios based on the evolution of the dynamic spillovers that has been detected.

To manage the potential adverse effects of extreme risk spillovers, policy makers can use appropriate policy tools and monitoring mechanisms based on our understanding of the effects of size and sign of spillover effects between insurance digital assets and conventional stocks. It will be impossible to formulate and implement stabilizing policies during extreme events if we focus only on average shocks within the interconnected system. So, this study contributes to the recent literature, further investigating different extreme quantiles in the interdependencies between digital and conventional assets, on extreme market states. In concrete, our findings show that bullish and bearish market states are asymmetric. Consequently, during extreme events in the insurance token market, institutional investors as well as individual traders would be able to participate and trade.

To address the limitations of this study, future research could broaden the scope of analysis by including a more diverse set of insurance digital assets and conventional stocks. This would allow for a more comprehensive understanding of spillovers within the insurance market and their potential impact on the broader financial system. In addition, extending the sample period beyond October 2022 would provide insights into how spillover effects have evolved over time and how they may continue to impact the market in the future (for example, in light of the Russian invasion of Ukraine). By addressing these limitations, future research could build upon the findings of this study and contribute to a deeper understanding of the dynamics of spillovers in the insurance market.

The study suggests that the two leading insurance tokens could be used as diversifiers or hedging instruments in investment portfolios, and portfolio managers should consider adjusting their portfolios based on the evolution of dynamic spillovers. Policymakers can use appropriate policy tools and monitoring mechanisms to manage the potential adverse effects of extreme risk spillovers. In addition, the study shows that bullish and bearish market conditions are asymmetric, allowing institutional investors and individual traders to participate and trade during extreme events in the insurance token market. Thus, if the interaction between insurance tokens and conventional stocks is significant during extreme market conditions, it could lead to contagion and amplification of risks across markets and financial institutions. Furthermore, this situation could create investment opportunities for investors who can identify undervalued assets or take advantage of market dislocations. Finally, the study's findings could have regulatory implications for financial institutions and policymakers. If the interaction between insurance tokens and conventional stocks poses a systemic risk, regulators may need to develop new rules or supervisory mechanisms to mitigate these risks.

Appendix

See Table A.1.

Table A.1
Static return spillovers at mean using Diebold and Yilmaz (2012) approach.

	NXM	SURE	UNH	ELV	AIA	PAI	CLIC	CGC	MMC	CB	FROM
NXM	70.28	6.84	2.97	2.41	2.42	2.02	1.88	2.62	5.25	3.30	29.72
SURE	8.42	76.79	2.40	2.04	2.23	1.58	2.22	1.08	1.40	1.84	23.21
UNH	2.07	1.05	37.07	24.55	0.86	0.94	0.83	17.19	9.17	6.28	62.93
ELV	1.58	1.10	24.42	37.73	0.63	0.94	0.76	18.77	7.30	6.78	62.27
AIA	1.37	2.25	1.93	2.51	53.67	15.57	16.09	1.53	3.11	1.97	46.33
PAI	1.08	0.93	1.65	2.02	13.55	46.80	25.10	2.92	3.50	2.45	53.20
CLIC	1.10	0.86	1.60	2.11	13.51	25.04	46.35	3.17	3.90	2.36	53.65
CGC	1.34	1.15	18.32	20.34	0.70	0.77	1.23	41.49	7.07	7.58	58.51
MMC	3.22	0.96	11.67	9.63	1.47	2.08	2.05	8.05	48.44	12.44	51.56
CB	1.87	1.10	8.18	9.08	1.16	1.70	2.14	9.94	12.65	52.18	47.82
TO	22.05	16.23	73.14	74.69	36.54	50.62	52.30	65.26	53.37	45.00	489.20
Inc.Own	92.33	93.03	110.20	112.42	90.21	97.42	98.66	106.75	101.81	97.17	TCI
NET	−7.67	−6.97	10.20	12.42	−9.79	−2.58	−1.34	6.75	1.81	−2.83	48.92

Notes: This table collects the static return spillovers at mean using Diebold and Yilmaz (2012) approach between insurance tokens (NXM—Nexus Mutual, SURE—inSure DeFi Price) and some insurance stocks (UNH—UnitedHealth Group Incorporated, ELV—Elevance Health Inc., AIA—AIA Group Limited, PAI—Ping An Insurance, CLIC—China Life Insurance Company Limited, CGC—Cigna Corporation, MMC—Marsh & McLennan Companies, Inc., CB—Chubb Limited) during the sample period between 21 July 2020 and 18 October 2022.

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