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Spillover dynamics in DeFi, G7 banks, and equity markets during global crises: A TVP-VAR analysis

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A B S T R A C T

Decentralized finance (DeFi) has become of significant interest for investors in both the financial and digital sectors. We use a time-varying parameter vector autoregression (TVP-VAR) approach to estimate the static and dynamic connections between and within DeFi, G7 banking, and equity markets. We focus on critical events such as the COVID-19 pandemic, the cryptocurrency bubble, and the Russia-Ukraine conflict. The results highlight interconnectedness and significant spillovers within and between the markets, especially during the COVID-19 pandemic. Notably, there were significant spillover effects from the G7 banking and equity markets to Japan and DeFi assets. The findings demonstrate a robust connection between DeFi platforms, G7 banking, and stock markets throughout these tumultuous periods. Policymakers, investors, and entrepreneurs are recommended to keep a close eye on changes in traditional banking and equity markets to adjust the risk of DeFi assets.

1. Introduction

Decentralized finance (DeFi) has risen as a formidable alternative to the traditional financial system, poised to radically alter the functioning of digital trading platforms shortly. Several studies have focused on the substantial cross-market dynamics of fifi-assets, crypto, and financial markets in recent crises (Cevik et al., 2022; Chowdhury et al., 2023; Corbet et al., 2023; Ugolini et al., 2023; Yousaf et al., 2023a; Yousaf and Yarovaya, 2022) and diversification benefits (Ali et al., 2023; Bennett et al., 2023). DeFi denotes a collection of decentralized, open-access, peer-to-peer (P2P) financial services and solutions underpinned by blockchain technology and smart contracts. This shift allows individuals to lend, borrow, and trade financial assets devoid of traditional intermediaries, thereby challenging the established operational frameworks of financial services by removing a single point of control or failure (Harvey et al., 2021). By Apr 2022, such advancements had escalated the market valuation of DeFi to an estimated 150 billion United States dollars,

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reflecting a surge of over fifty percent in the total value locked in DeFi from the preceding year (Yousaf et al., 2023a).

Statistically, a significant number of platforms and exchanges that enable the sale, purchase, and exchange of virtual currencies, coins, and other digital assets are user friendly, free, and app based. Only a basic smartphone and a web connection are required to access it (Bennett et al., 2023). The LINK-Chain-link, MKR-Maker, and BAT-Basic Attention Tokens comprise only a few DeFi assets. A Chain-link token called LINK makes payments to the network operators at the nodes. MKR is the governance token of the Ethereum-based Maker DAO and Maker Protocol, which enables users to create and control the DAI stablecoin. BAT is the native coin of the Brave web browser. It operates on the Ethereum blockchain and provides clients with a tiny reward for seeing advertisements on other websites (Yousaf et al., 2023a).

However, banking and stock markets are integral to the economy and collaborate to enhance economic growth. Banks, holding significant stakes in a multitude of companies and providing loans to corporations, are key actors in enabling businesses to raise capital and grow (Beckett et al., 2000). Thus, the banking industry's performance significantly influences the stock market. For instance, banks may curtail lending to businesses during economic recessions, potentially triggering a decline in economic activity and a consequent fall in stock prices. Some recent studies have also focused on G-country banking sector cross-market dynamics in crises (Apostolakis et al., 2022a; Aydoğan et al., 2022; Younis et al., 2024).

Theoretically, an inverse relationship exists between the stock market and the banking sector; higher interest rates may increase borrowing costs for businesses, possibly leading to a decrease in stock prices. Predicting the stock market's response to developments in the banking sector is complex because of its interconnectedness, as illustrated by the 2008 financial crisis. Therefore, shifts in a country's banking industry have global implications for the stock market. Nonetheless, an understanding of the dynamics between these two sectors can aid investors in making informed investment choices.

This study empirically investigates the dynamic spillover effect of DeFi, the G7 countries' banking sector, and the stock market in two panels: COVID-19 and RUW. The G7 countries, which include the United States, Canada, France, Germany, Italy, Japan, and the United Kingdom, comprise seven nations with the strongest economies globally. These economies account for 58% of the world's net worth (IMF 2018). The purpose of this forum is to discuss financial and economic matters among leading industrialized nations. G7 is made up of developing nations with room to expand and invest. The way banking services and goods are provided changes due to technological advancements. The loan, investment, and payment services industries have undergone a significant transformation as a result of the introduction of cutting-edge platforms, interfaces, and payment options such as DeFi. However, these prospective advantages do not materialize until substantial risks are addressed. These economies are not without their difficulties. In 2023, Shunichi Suzuki, the Minister of Finance, stated that the emergence of social media and online banking has significantly changed the financial environment(World Economic Forum).[2] These technological developments have changed the way consumers use financial services, obtain information, and conduct transactions. Every nation on the planet faces these challenges. As a result, the main goal of this study is to determine how the DeFi, banking, and stock markets of the G7 countries interact.

Notably, the robustness of traditional banking and stock markets is well established and undiminished by the advent of DeFi, a fact underscored by comprehensive academic inquiries. Discussions persist regarding the measurable effects of changes within the banking sector, financial market operations, and the burgeoning DeFi framework on economic development (Yousaf et al., 2023c). Notwithstanding, the literature has minimally explored the repercussions of emerging financial innovations, such as DeFi assets on both the banking industry and stock market portfolio returns. This investigation is poised to scrutinize the banking sector of G7 nations, advancing a scholarly review pertinent to this sphere. While various studies have delved into the interplay between DeFi and financial assets amid economic downturns (Apostolakis et al., 2022b), our study contributes to the current literature in several ways.

Our study contributions are multifaceted; first, our study analyzed the innovative links between traditional banking sectors, the financial market, and new banking assets, such as DeFi assets, particularly in the context of G7 countries in crisis. This research contributes to the field of digital and traditional financial markets' risk-return spillovers and interconnectedness and differs from previous studies in the context of defi-assets and mixed market dynamics (Alam et al., 2023; Ali et al., 2023; Bennett et al., 2023; Chohan, 2021; Chowdhury et al., 2023; Karim et al., 2022). However, our study classifies defi-assets with G7 countries that have influential banking institutions that are crucial to their respective financial systems. It is crucial to assess the potential impacts and interactions between decentralized finance and traditional banking systems during crises. Second, our study contributes to financial asset flows and their risk-return spillovers and contingent effects among the G7 banking indices because they have significant funding sources for governments and enterprises and are crucial to the global economy. Several previous studies have focused on the defi-assets portfolio mix (Ali et al., 2023), defi-financial inclusion (Abdulhakeem and Hu, 2021), and defi-future (Harvey et al., 2021), but our study differs from previous studies (Aydoğan et al., 2022; Balcilar et al., 2022; Yousaf and Yarovaya, 2022). Further, due to the risk-return interconnections between DeFi and the G7 banking and equity markets, the financial system may become more innovative and efficient. This relationship may significantly increase both transmission and volatility in the event of a financial crisis events. Finally, our study contributes to the analysis and methodology of some of the most recent studies using this approach (Adekoya and Oliyide, 2021; Apostolakis et al., 2022a; Aydoğan et al., 2022; Cao and Xie, 2022). Besides, we utilize time-varying parameter vector auto-regressions (TVP-VAR) following (Antonakakis et al., 2020a). Previous studies examine spillovers across assets and markets using Granger causality, conditional correlation, conditional VAR, and estimations (Diebold and Yilmaz, 2012; Diebold and Yılmaz, 2014). The TVP-VAR method effectively captures the overall connectedness and dynamics of cross-assets and cross-country connectedness structures. It overcomes the issue of connectedness measures based on variance decomposition on an arbitrary rolling window size.

[2] https://www.weforum.org/agenda/2023/05/us-debt-default-g7-financial-system-plus-other-economy-stories-you-need-to-read/

Further, we also estimate DeFi-assets, G7-banking, and stock returns connectedness for the robustness of static spillover results by using the 20-day forecast horizon instead of 10 days (see Table A1 in the appendix). Robustness checks confirmed the baseline results (Yousaf et al., 2023c).

The study outcomes reveal that DeFi assets, banks, and stock markets (G7) were strongly interconnected during COVID-19, the crypto bubble, and RUW. Defi assets and Japan are the higher volatility risk receivers of market shocks and COVID-19. Further, the banking and equity markets of Canada, France, Germany, Italy, the United States, and the United Kingdom have higher spillover transmissions to Japan and DeFi assets. This study employed the TVP-VAR model to analyze both constant and fluctuating return spillovers between DeFi investments and the G7 banking and equity markets. The findings suggest a significant linkage between DeFi and the G7 financial sector, highlighting DeFi's integral role in the global financial ecosystem. This study underscores the importance of understanding the static and dynamic relationships among DeFi, G7 banks, and stock markets to understand the modern financial landscape. This research has important implications for investors, governments, and market participants, emphasizing the need for awareness of the potential risks and spillover effects between DeFi and traditional finance, particularly during financial crises. The remainder of this paper is structured as follows: a literature review in Section 2, data and methodology in Section 3, findings in Section 4, and conclusions in Section 5.

2. Literature Review

In the contemporary era, marked by blockchain innovations, scholarly inquiry into the volatility spillovers and network connectedness of financial assets has been extensive (Cao and Xie, 2022). COVID-19 and RUW have notably impacted financial markets globally, regionally, and nationally. Previous studies have highlighted an augmented spillover among stock markets in times of crises. A comprehensive examination of the DeFi, banking, and stock markets of the G7 countries is revealed by a synthesis of the existing literature. This study focuses on the spillover effect among these sectors and their strategic importance in investment portfolios, which is further highlighted by a wide range of econometric methods and models. The literature can be divided into various categories. The author begins by discussing research on spillovers among stock markets, which has been conducted using a variety of econometric techniques. The banking industry is discussed in the second section. The third section discusses Defi and covers the research questions.

Savva et al. (2009) included the US, UK, German, and French stocks as variables to analyze the stock market's spillover effect using VAR-ADCC-MEGARCH. Arouri et al. (2012) used VAR-MGARCH to analyze the volatility effects between European sector stocks and crude oil. Weber and Zhang (2012) conducted a market research in China. They used VAR-SDCC and VECM-SDCC Models to investigate Chinese A-, B-, and H-shares. Their findings demonstrate that the magnitudes and orientations of the spillovers between Chinese A-, B-, and H-shares significantly changed after the B-share market opened to Chinese citizens in 2001. Chang et al. (2013) investigated that there were few significant volatility spillovers between US and UK equities and crude oil. After the US financial crisis, Bekiros (2014) used BEKK-CCC-DCC-MGARCH techniques to establish a connection between the US, EU (Germany), and BRIC stock markets. Kim et al. (2015) investigated how the US financial crisis 2008 had a negligible impact on the exchange rates and stock markets of Indonesia, Korea, the Philippines, Taiwan, and Thailand, even though the spillover effects in these emerging Asian countries were fleeting. Kundu and Sarkar (2016) examined the spillover effect between the US, UK, and BRIC markets using daily data from 2000 to 2012. Huo and Ahmed (2017) discovered that volatility spillovers from Shanghai to Hong Kong grew following Shanghai-Hong Kong Stock Connects. Gamba-Santamaria et al. (2017) created volatility spillover indices for the US and four Latin American stock markets by expanding the framework of Diebold and Yilmaz (2009), (2012) and including a DCC-GARCH model. Brazil is typically reported to be a net volatility transmitter. Furthermore, COVID-19 ecological disasters began to affect the planet at the end of 2019. According to Elsayed et al. (2020), the world energy index and world stock index are the main sources of volatility on spillovers among the seven international financial markets.

Consequently, the banking sector risk-return spillovers and link behaviors have been addressed excessively in previous studies. Elyasiani and Mansur (2003) used MGARCH to examine the relationship between the volatility of the US, German, and Japanese banking sector equities. They discovered that interest rate volatility and unsystematic shocks significantly affect the spillover effect from one economy to another. Brailsford et al. (2006) found that major banks' shareholdings spilled to smaller ones in Taiwan, China, and Hong Kong. Given the importance of banks in currency exposure, Gounopoulos et al. (2013) examined the connection between stock market returns and currency risk for banking and insurance providers in three significant countries: the US, the UK, and Japan. The VAR BEKK-M GARCH model was employed in this study. Their primary focus was on the 2008 financial crisis, when US banks showed a negative association with changes in the Japanese yen. The following year, Choudhry and Jayasekera (2014) investigated not only the banking sector of the countries studied by Gounopoulos et al. (2013), but also Germany and European Union (EU) countries. Using a bivariate GJR-GARCH model, they discovered unidirectional return spillover effects from countries such as the US, the UK, and Germany to European Union nations during the pre-crisis period of the GFC. Elyasiani et al. (2015) employed an expanded VAR-BEKK-MGARCH model and found that the US banking and insurance sector was the strongest and most important transmitter. Allegret et al. (2017) utilized a multifactor model using smooth transition regression to assess the impact of the European sovereign debt crisis on banking stock market returns in fifteen distinct countries. Their findings demonstrate that the sovereign debt crisis harmed European banks and did not affect US banks. Moudud-Ul-Huq (2021) investigated the relationship between capital buffer, risk, and efficiency adjustments using GMM and demonstrated that the changes in capital holding, risk, and efficiency were significantly impacted by the cycle of economic activity. Additionally, owing to the implementation of regulatory pressure, large-funded banks had lower efficiency than low-funded banks. Stewart and Chowdhury (2021) also examined the impact of the health of banks, the availability of funds, and equity on the association between output growth and bank crises using GMM panel data. Wang et al. (2021)

suggest multilayer information spillover networks among 30 Chinese financial institutions from 2011 to 2018 and found that at the individual level, institutions from various financial sectors play different roles in receiving or sending shocks based on various information spillover or contagion channels. Furthermore, some studies explore the impact of COVID-19 on Islamic and conventional bank stocks. Focusing on the performance of bank stocks, Mirzaei et al. (2022) find that during early COVID-19, IB stock returns performed better than CB stock returns. According to Ashraf et al. (2022), after the COVID-19 market collapse, stock market investors in GCC countries did not perceive IBs in GCC countries as superior to CBs and both IBs and CBs were adversely impacted. Another study indicated that deregulation increased stock market liquidity, particularly for borrowers with weak ex-ante monitoring and screening, whereas banking expansion promoted the health of equity markets (Gallimberti et al., 2022). Conversely, Almahadin ((Almahadin, 2022) empirical results show that local interest rate volatility has detrimental effects on Asian countries' banking sectors. As a result, interest rate risk threatens Asian banking sector stocks. These studies of the banking industry present a varied picture of the banking sector's global spillover effect. It also indicates that there is much more possibility for further research in the banking industry of various nations that is yet to be explored. The available literature also suggests that more practically suitable models can be used to capture genuine spillover effects.

Some new studies have focused the market returns during COVID-19 pandemic (Adekoya et al., 2021; Chakraborty and Maity, 2020; Umar et al., 2021; Zhang et al., 2023). Furthermore, digital assets are used as a hedge against stock market declines and have a low correlation with financial and commodity markets(Cao and Xie, 2022; Guesmi et al., 2019). However, Ugolini et al. (2023) found significant return spillovers inside and between marketplaces in the DeFi and cryptocurrency markets. Safe-haven assets are insignificant absorbers and transmitters of the spillover effects between markets. According to Piñeiro-Chousa et al. (2022), DeFi tokens act as a safe-haven asset against the volatility of the stock market. Statistically, the Google Trends Index, the S&P100, the crude oil, and the gold volatility index revealed that COVID-19 significantly impacts the dynamic overall connectedness (Apergis et al., 2023). Further factors influencing DeFi token pricing, examining the relationship and correlation between Google Trends, Ethereum, and Bitcoin, revealed that DeFi is a distinct asset class from other prominent cryptocurrencies (Corbet et al., 2022). Notably, investors consistently experience worry about suffering losses in their assets during economic, financial, or health crises.

Scholarly research has extensively explored the dynamics between cryptocurrency, hedging ratios, stock markets, commodities, and the banking sector (Patel et al., 2022). However, studies on decentralized finance (DeFi) remain relatively scarce. Despite the nascent state of the DeFi and G7 stock markets and their limited scrutiny, they have seen substantial growth in market capitalization as assets that mitigate risk. Factors influencing the DeFi market and stock prices include the evolution of blockchain technology, emerging protocols and products, supply and demand dynamics, and shifting investor sentiment towards the DeFi ecosystem (Corbet et al., 2022). Although DeFi exhibits high volatility and has experienced significant growth, its rapid price fluctuations of DeFi assets underscore its potential unpredictability. The nascent nature of these markets, characterized by limited liquidity, contributes to their pronounced volatility (Alam et al., 2023).

Several studies have observed the cross-markets effects during the Russia-Ukraine geopolitical conflicts(Deng et al., 2022; Jiang and Chen, 2024; Kuzemko et al., 2022; Sun et al., 2022; Umar et al., 2022b; Yousaf et al., 2022; Zhang et al., 2023). Further, academicians have extensively researched volatility spillover in the modern environment when risk presents an opportunity (Arouri et al., 2011; Kang et al., 2019). However, the relationship between DeFi, banking, and the stock market of G7 countries is not well understood in the literature, even though the terms "Defi," banking, "financial market," and "G7" have long been linked to economic expansion. Our empirical results are expected to provide information on the strength or weakness of the spillover between the stock market and the traditional decentralized banking system. It also has policy implications for reaching SDG 17, partnerships for the goals that aim to improve how the Global Partnership for Sustainable Development is implemented and revitalized in the area of finance and financial inclusion. Moreover, this study aims to add to the growing body of work by employing unique statistical methods to examine the beneficial and detrimental spillover effects between DeFi and G7 stocks and banks. We employ the unique TVP-VAR estimation strategy, which is a variant of Diebold and Yilmaz's mean-based vector autoregression (VAR) technique. The return-spillover nexus has been studied using a mean-based connection approach. This study examines information flow patterns during shocks such as COVID and RUW and gives investors recommendations on how to adjust their asset allocation because hedging qualities could alter. Research on crisis times is likely to produce substantial evidence on DeFi shock features, traditional banking, and market interactions, such as how markets respond to extreme events.

In general, DeFi's inclusion in a portfolio dominated by the stock market and traditional banking is meant to address the following two questions: (i) Do Defi stocks spillover over the traditional banking system? (ii) In what ways might DeFi enhance the stock market and banking performance of conventional portfolios? Our fresh research is different from the previous studies in terms of mixed markets and Defi-assets dynmaics (Alam et al., 2023; Ali et al., 2023; Bennett et al., 2023; Chohan, 2021; Chowdhury et al., 2023; Karim et al., 2022). Several previous studies have focused on the defi-assets portfolio mix (Ali et al., 2023), fi-financial inclusion (Abdulhakeem and Hu, 2021), defi-future (Harvey et al., 2021), and cross-markets in crisis (Aydoğan et al., 2022; Balcilar et al., 2022; Yousaf and Yarovaya, 2022), but our study differs from previous studies. Nonetheless, our analysis links debt assets with the G7 nations that have significant banking institutions that are essential to their financial systems. Furthermore, due to the risk-return portfolio benefits between DeFi and the G7 banking and equity markets, the financial system has become more innovative. By using TVP-VAR (Adekoya and Oliyide, 2021; Apostolakis et al., 2022; Aydoğan et al., 2022; Cao and Xie, 2022); our study exploring fresh and innovative spillover dynamics between DeFi, G7 banking sector and equity markets during crisis.

3. Data and methods

3.1. Data and preliminary analysis

We selected the G7 (The United States, Canada, the United Kingdom, Germany, France, Italy, and Japan), a group of the world's largest economic banks (Matos et al., 2021), based on their ability to strengthen the global financial system and the daily incorporation of their closing share price into the index creation process. Because investors are shifting their attention from their local markets to developed economies to construct diverse global portfolios, this study includes the MSCI stock market (Aydoğan et al., 2022; Chiang, 2019), representing the G7 countries as an additional set of variables under investigation. To represent the DeFi assets, chainlink (LINK), Basic Attention Token (BAT), and maker (MKR) (Ali et al., 2023; Yousaf et al., 2023a; Yousaf and Yarovaya, 2022) are considered.

This study used the daily price series of each of the 17 variables. Three Defi asset data collected from www.coinmarketcap.com and G7 banking sectoral index (The United States (BANKSUS), Canada (BANKSCN), the United Kingdom (BANKSUK), Germany (BANKSGER), France (BANKSFR), Italy (BANKSIT), and Japan (BANKSJP)) and MSCI stock markets (The United States (MSCIUS), Canada (MSCICN), the United Kingdom (MSCIUK), Germany (MSCIGER), France (MSCIFR), Italy (MSCIIT), and Japan (MSCIJP)) data were collected from Data Stream. The daily prices of each series returns are estimated as $\ln(pt/pt-1) \times 100$. The period from Dec 2019 to Oct 2022 is suitable for research because it encompasses the development and worldwide effects of COVID-19, the rise and collapse of the crypto bubble, and the changing dynamics of the Russo-Ukrainian War, providing thorough knowledge of these momentous events. This period was divided into four Panels: Panel A=Jan-Dec 2020 (COVID-19); Panel B=Jan-Dec 2021 (Crypto bubbles), Panel C= Feb-Oct 2022 (Russian-Ukraine War) (Yousaf et al., 2023b) Panel D= Dec 2019 to Oct 2022 (Overall target sample). During these three vital events, this study examines different economies, such as the banking sector and equity with DeFi assets. Table 1 presents the descriptive statistics for the four research timeframes. As Panel A shows, the MSCIUS, MACIUK, MSCIJP, and LINK indices display a negative return mean. The mean returns of all the banking indices are positive. LINK returns have the largest negative value, whereas the MRK index has the highest mean return. Among the DeFi assets, the MKR index had the largest variance, followed by LINK and BAT. Compared to DeFi assets, fluctuations in the banking sector and stock market indices are insufficient. The Jarque-Bera statistic test, which assesses the kurtosis and skewness of time-series data, is highly significant. Positive skewness exists in each series. This implies that the time-series data are skewed to the right. Overall, the findings in Table 1 suggest that DeFi assets are more volatile than banking sector and stock market indices. In addition, time-series data for all assets are not normally distributed.

3.2. Econometric modelling framework TVP-VAR

In previous literature on connectedness dynamics, the linkage structure was primarily evaluated using standard time-series models. A major shortcoming of these approaches is that they do not fully consider the possibility of dependency shifting based on the frequency of price fluctuations. For the interconnectedness analysis of the Defi, Equity, and Banking Sector Indices of G7 nations, we combine the connectivity technique of Diebold and Yilmaz (2009), (2012) with the TVP-VAR paradigm, which was developed by Koop and Korobilis (2014). Baruník et al. (2016) and Antonakakis et al. (2020b) subsequently Antonakakis et al. (2020b); Baruník et al. (2016) improved this method. The TVP-VAR approach has been used in several studies because of its substantial analytical benefits (Adekoya and Oliyide, 2021; Cao and Xie, 2022; Mishra and Ghate, 2022; Nham, 2022; Younis et al., 2024; Younis et al., 2023).To calculate the overall connection, paired connectivity, connectivity from each market to the framework, interconnectivity across every sector to the framework, and net connectedness, we employed the TVPVAR framework. The key benefit of this method lies in the use of a Kalman filter calculation that depends on decaying factors that enable the variances to fluctuate with time. Thus, the TVP-VAR method avoids the drawbacks of an arbitrary rolling window size, which results in excessively irregular or flattened values and loss of important information. In addition, this approach can evaluate dynamic interconnectedness using limited time-series data. The TVP-VAR strategy can be expressed as

$$y_t = \beta_t z_{t-1} + \in_t; \in_t | F_{t-1} \sim N(0, \quad S_t) \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + v_t; v_t | F_{t-1} \sim N(0, \quad R_t) \tag{2}$$

where y_t and $z_t = [y_{t-1}, \ \ldots \ , y_t - p]'$ represent $N \times 1$ and $P \times 1$ dimensional vectors, respectively. β_t is an $N \times N_p$ dimensional time-varying coefficient matrix and ϵ_t is a $N \times 1$ dimensional error disturbance vector with an $N \times N$ time-varying variance-covariance matrix S_t, $vec(\beta_t)$ and $v_t$are $N_p^2 \times 1$ dimensional vectors and R_t is an $N_p^2 \times N_p^2$ dimensional matrix. The next step involves the computation of generalized impulse response functions (GIRF) and generalized forecast error variance decomposition (GFEVD). This is done by applying the vector moving average (VMA) model to the VAR system following the methodology outlined by Koop et al. (1996) and Pesaran and Shin (1998):

$$y_t = \sum_{j=0}^{\infty} L' W_t^j L \in_{t-j} \tag{3}$$

$$y_t = \sum_{j=0}^{\infty} A_{it} \in_{t-j} \tag{4}$$

where $L = [I_N, \ \ldots \ , 0_p]'$ is an $N_p \times N$ dimensional matrix, $W = [\beta t; I_{N(p-1),} \quad 0_{N(p-1)\times N}]$ is an $N_p \times N_p$ dimensional matrix,

Table 1
Summary of Statics.

	LINK	BAT	MKR	BANKSCN	BANKSFR	BANKSGER	BANKSIT	BANKSJP	BANKSUS	BANKSUK	MSCICN	MSCIFR	MSCIGER	MSCIIT	MSCIJP	MSCIUS	MSCIUK
Panel A: COVID-19																	
Mean	-0.361	0.248	0.331	0.036	0.171	0.112	0.121	0.106	0.145	0.192	0.019	0.044	0.02	0.058	-0.015	-0.044	0.084
Variance	78.406	59.301	129.817	6.043	12.674	7.265	7.653	2.93	12.257	6.983	4.592	4.198	4.042	5.292	1.891	4.751	3.434
Skewness	4.146***	4.200***	8.752***	0.630***	0.865***	0.954***	1.902***	0.837***	0.541***	0.258*	1.759***	1.454***	1.493***	3.349***	0.111	1.272***	1.264***
Ex.Kurtosis	39.844***	39.540***	114.053***	13.550***	5.194***	4.358***	12.769***	5.506***	4.648***	3.154***	17.364***	10.224***	11.844***	27.353***	4.196***	10.038***	9.066***
JB	18012.290***	17769.358***	144796.104***	2013.823***	326.012***	246.090***	1930.383***	360.139***	247.615***	111.103***	3413.659***	1228.775***	1622.576***	8624.482***	192.034***	1166.252***	963.351***
ERS	-5.346***	-3.340***	-7.175***	-5.450***	-4.384***	-2.124**	-3.092***	-7.072***	-6.821***	-4.693***	-4.807***	-4.294***	-4.094***	-3.822***	-6.882***	-5.116***	-4.393***
Q(10)	14.846***	20.674***	21.317***	38.572***	13.346**	7.544	25.510***	7.986	35.976***	8.876	57.593***	21.489***	21.259***	25.056***	8.823	85.606***	16.135***
Q2(10)	5.647	2.104	2.138	190.814***	68.058***	40.691***	41.007***	25.542***	152.810***	18.369***	163.694***	51.207***	32.438***	26.349***	62.244***	194.992***	47.453***
Panel B: Crypto Bubbles																	
Mean	0.676	0.756	0.664	0.114	0.205	0.146	0.171	-0.006	0.15	0.107	0.066	0.076	0.151	0.118	0.009	0.104	0.037
Variance	45.631	39.072	45.22	1.227	5.595	8.817	6.933	1.498	3.579	3.426	1.116	2.12	2.489	2.783	1.331	2.551	1.153
Skewness	1.541***	1.273***	0.824***	0.293*	0.453**	0.715***	0.683***	0.205	-0.248	0.391**	0.175	-0.332*	-0.413**	0.315*	-0.145	0.300*	0.358**
Ex.Kurtosis	6.056***	4.796***	5.136***	0.536	2.644***	2.099***	3.332***	1.094**	0.188	1.894***	0.055	2.398***	2.239***	2.017***	0.289	-0.095	2.038***
JB	365.550***	233.374***	230.370***	4.992*	61.831***	51.066***	102.675***	10.802***	2.223	33.247***	0.989	49.003***	45.091***	35.351***	1.324	2.913	36.947***
ERS	-3.040***	-4.815***	-6.392***	-2.842***	-5.015***	-4.501***	-3.184***	-1.516	-6.003***	-3.908***	-5.204***	-5.133***	-5.628***	-4.325***	-1.611	-3.848***	-3.788***
Q(10)	5.036	10.015*	5.32	7.222	9.681*	4.744	6.214	4.26	2.199	3.477	5.328	3.423	3.118	4.037	4.027	3.854	5.08
Q2(10)	13.872***	28.850***	3.876	6.15	59.122***	46.365***	54.040***	9.033	4.707	42.021***	15.319***	35.826***	27.863***	43.172***	7.919	5.441	28.138***
Panel C: Russia-Ukraine War																	
Mean	0.146	-0.32	-0.202	-0.107	-0.124	-0.068	-0.101	-0.07	-0.095	-0.067	-0.075	-0.088	-0.038	-0.066	-0.037	-0.083	-0.051
Variance	72.98	72.538	64.942	0.437	2.312	3.347	1.817	1.52	2.151	2.185	0.428	0.7	0.734	0.955	0.983	0.693	0.627
Skewness	1.719***	0.509***	-0.092	0.639***	0.274*	0.257*	0.327**	-0.063	0.076	0.08	0.477***	0.968***	0.539***	0.684***	0.151	0.398***	0.476***
Ex.Kurtosis	9.143***	4.311***	3.128***	2.229***	1.345***	2.162***	1.472***	0.414	0.476	5.074***	1.453***	4.408***	2.160***	3.011***	0.464	0.839**	3.624***
JB	1033.587***	212.570***	106.382***	71.520***	22.830***	53.484***	28.102***	2.026	2.711	279.131***	32.725***	251.092***	63.150***	118.485***	3.315	14.489***	152.130***
ERS	-2.129**	-3.553***	-1.236	-4.420***	-4.933***	-3.037***	-6.407***	-3.883***	-3.969***	-2.901***	-5.249***	-3.728***	-7.292***	-6.704***	-5.168***	-2.018**	-1.398
Q(10)	10.935**	4.804	18.731***	8.629	5.76	4.28	3.354	10.189*	1.054	7.281	3.36	11.495**	15.203***	6.848	6.954	5.033	11.861**
Q2(10)	15.699***	7.085	19.431***	35.910***	2.62	2.812	7.73	18.253***	3.756	1.226	52.236***	7.096	9.986*	4.607	14.932***	45.235***	2.587
Panel C: Overall Target Sample																	
Mean	1.048	-0.374	3.055	3.652	2.593	1.74	2.7	2.101	3.166	3.36	3.365	3.326	2.994	2.861	3.041	3.563	3.287
Variance	0.129	0.081	0.12	0.006	0.01	0.005	0.005	0.003	0.008	0.006	0.003	0.003	0.003	0.003	0.002	0.005	0.002
Skewness	-0.447***	0.203**	-0.015	-0.506***	-0.678***	-0.471***	-0.417***	-0.504***	-0.587***	-0.628***	-0.782***	-0.802***	-0.717***	-0.698***	-1.011***	-0.682***	-0.694***
Ex.Kurtosis	-0.738***	-1.213***	-1.311***	-0.815***	-0.540***	-0.436***	-0.432***	-1.116***	-0.909***	-0.385***	0.222	-0.123	0.157	-0.261	0.204	-0.158	-0.507***
JB	42.218***	51.411***	54.012***	53.019***	66.843***	33.869***	27.703***	71.050***	69.291***	54.185***	78.392***	81.221***	65.377***	63.423***	129.732***	59.158***	68.604***
ERS	-0.382	-0.99	-0.886	-0.921	-1.506	-2.290**	-1.903*	-1.361	-1.171	-0.821	-1.242	-1.742*	-1.854*	-1.946*	-1.135	-0.566	-1.629*
Q(10)	3950.572***	3974.379***	4014.548***	4064.676***	3920.342***	3771.405***	3832.332***	3901.334***	3971.193***	3944.801***	3988.477***	3948.855***	3830.676***	3855.865***	3973.494***	4008.768***	3873.418***
Q2(10)	3952.221***	3900.742***	4017.461***	4067.829***	3925.470***	3765.668***	3834.796***	3903.296***	3975.534***	3943.994***	3993.585***	3953.447***	3838.297***	3861.383***	3974.816***	4011.377***	3877.210***

Note: This table presents the basic summary statistics of defi, G7 banking and stock indices returns for full sample ((Jan, 19 to Oct, 22), COVID-19 (Jan, 20 to Dec, 20), Crypto market crash (Jan, 21 to Dec, 21) and Russia-Ukraine war (Jan, 22 to Oct, 22). ***, **, * denote significance at 1%, 5% and 10% level.

and A_{it} is an $N \times N$ dimensional matrix. The GIRFs illustrate the reactions of the individual variables to a disturbance in variable i. This variation is believed to be induced by a disturbance in variable I; as such, it is determined through the following calculation:

$$GIRF_t(K, \quad \delta_{j,t}F_{t-1}) = E(y_{t+K}|\in_{j,t} = \delta_{j,t}F_{t-1}) - E(Y_{t+K}|F_{t-1}) \tag{5}$$

$$\psi^g_{j,t}(K) = \quad \frac{A_{K,t}S_t\in_{j,t}}{\sqrt{S_{j,j,t}}} \quad \frac{\delta_{j,t}}{\sqrt{S_{j,j,t}}} \quad \delta_{j,t} = \sqrt{S_{j,j,t}} \tag{6}$$

$$\psi^g_{j,t}(K) = \quad \frac{A_{K,t}S_t\in_{j,t}}{\sqrt{S_{j,j,t}}} \tag{7}$$

In this context, $\psi^g_{j,t}$ represents the Generalized Impulse Response Functions (GIRFs) for variable j, with K indicating the forecast horizon. $\delta_{j,t}$ is a selection vector that has a value of one in the jth position and zero elsewhere, while F_{t-1} denotes the information available up to the time point t-1.

Subsequently, the Generalized Forecast Error Variance Decomposition (GFEVD) can be computed, which quantifies the proportion of variance that one variable holds over the others using the following method:

$$\widetilde{\Phi}^{\,g}_{ij,t}(K) = \frac{\sum_{t=1}^{K-1}\Psi^{2,g}_{j,t}}{\sum_{j=1}^{N}\sum_{t=1}^{K-1}\Psi^{2,g}_{j,t}};\sum_{j=1}^{N}\widetilde{\Phi}^{\,g}_{ij,t}(K) = 1\text{and}\sum_{j=1}^{N}N^g_{ij,t}(K) = N \tag{8}$$

Using Eq. (7), we establish a comprehensive connectivity index, which can then be employed to explore the impact of one stock market index on another index under examination.

$$C^g_t(K) = \frac{\sum_{i,j=1 i\neq j}^{N}\widetilde{\Phi}^{\,g}_{ij,t}(K)}{N} * 100 \tag{9}$$

Examining directional connectivity is intriguing. The method in question considers three aspects in this direction. Initially, it characterizes the total directed connectivity to other elements as follows:

$$C^g_{i\to j,t}(K) = \frac{\sum_{i,j=1 i\neq j}^{N}\widetilde{\Phi}^{\,g}_{ij,t}(K)}{\sum_{i,j=1}^{N}\widetilde{\Phi}^{\,g}_{ij,t}(K)} * 100 \tag{10}$$

Second, the complete directional connectedness originating from other sources is expressed as

$$C^g_{i\leftarrow j,t}(K) = \frac{\sum_{i,j=1 i\neq j}^{N}\widetilde{\Phi}^{\,g}_{ij,t}(K)}{\sum_{j=1}^{N}\widetilde{\Phi}^{\,g}_{ij,t}(K)} * 100 \tag{11}$$

The net overall directional connectedness can be determined by subtracting Eq. (11) from Eq. (10) as follows:

$$C^g_{i,\quad t}(K) = C^g_{i\to j,t}(K) - C^g_{i\leftarrow j,t}(K) \tag{12}$$

To delve deeper into the bidirectional connections, we employ the subsequent formula to calculate the Net Pairwise Directional Connectedness (NPDC):

$$NPDC_{i,j}(K) = \quad \widetilde{\Phi}^{\,g}_{ij,t}(K) - \widetilde{\Phi}^{\,g}_{ji,t}(K) \tag{13}$$

In line with Eq. (13), a positive NPDC value signifies that the stock values in index i are primarily influenced by those in index j, whereas a negative NPDC value indicates a reverse scenario.

4. Results and discussion

A network connectedness TVP-VAR model was used for the analysis (Diebold and Yilmaz, 2009, 2012). For the period from Jan 2020 to Oct 2022, the model is evaluated for return spillovers across the DeFi assets, banking, and equity indices of G7 economies. The outcomes clearly show how COVID-19, the cryptocurrency bubble, and the Russian-Ukrainian war have affected returns related to DeFi assets, banking, and equity indices of G7 countries.

4.1. Averaged returns static connectedness

The analysis of averaged total time-varying (averaged total returns) spillovers between the banking sector, the G7 equity market, and DeFi assets is presented in Fig. 1a, b, c, and d. The COVID-19 crises' time-varying volatility from Jan 1, 2020, to Dec 31, 2020, is depicted in Fig. 1a. The volatility of the cryptocurrency crises from Jan 1 to Dec 31, 2021, is depicted in Fig. 1b as changes over time. Fig. 1c illustrates the time-varying volatility of the Russian-Ukrain War, from Jan 1 to Oct 31, 2022. Lastly, Fig. 1d the period from Jan 1, 2020, to Oct 31, 2022.

Fig. 1a that the COVID-19 Crisis-related volatility had nearly reached 80% by the end of Feb 2020. The World Health Organization (WHO) designated the COVID-19 epidemic, which began on Mar 11, 2020, as a global pandemic. As an outcome, a large rise in return

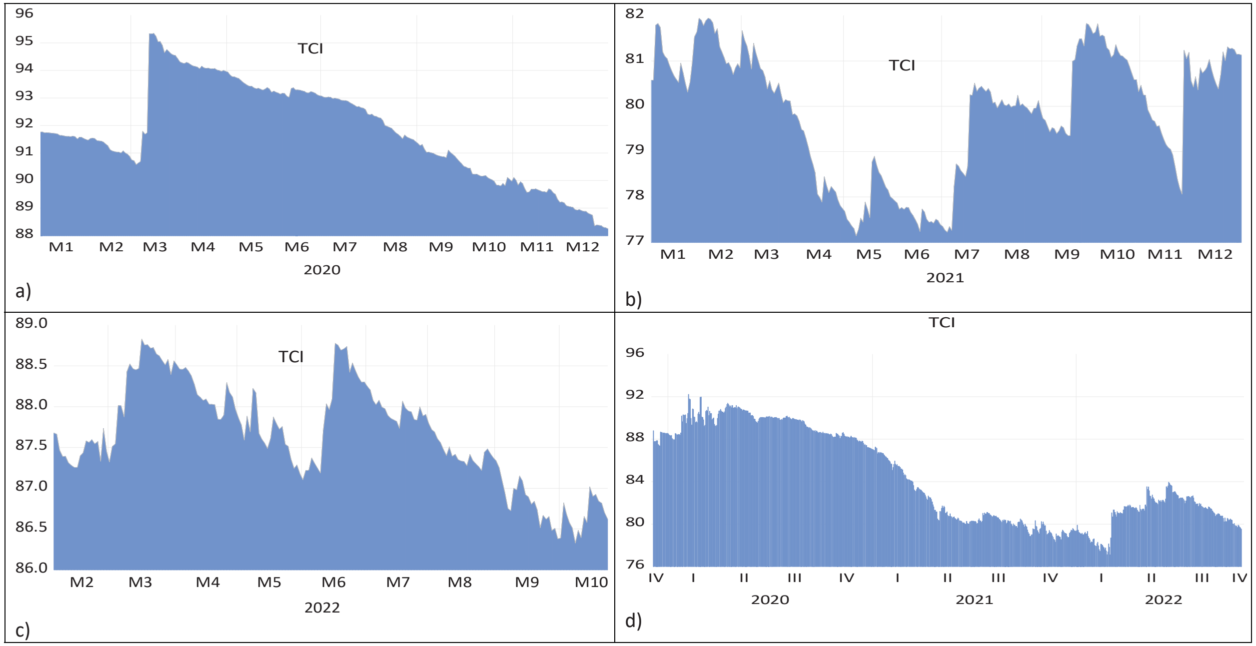

Fig. 1. This fig presents the basic total connectedness between defi, G7 banking and stock indices returns for COVID-19 (a=Jan, 20 to Dec, 20), Crypto market crash (b=Jan, 21 to Dec, 21), Russia-Ukraine war (c=Jan, 22 to Oct, 22) and full sample (d=Jan, 19 to Oct, 22).

Table 2
Dynamic Averaged Returns Connectedness.

	LINK	BAT	MKR	BANKSCN	BANKSFR	BANKSGER	BANKSIT	BANKSJP	BANKSUS	BANKSUK	MSCICN	MSCIFR	MSCIGER	MSCIIT	MSCIJP	MSCIUS	MSCIUK	FROM
Panel A: Covid-19																		
LINK	22.13	13.38	13.64	3.17	3.37	3.5	5.62	0.82	2.06	2.48	4.59	4.23	4.54	6.69	1.35	4.31	4.12	77.87
BAT	11.86	20.8	11.44	3.58	3.56	3.6	5.75	1.63	2.56	2.61	5.37	4.42	5	6.71	2.01	4.87	4.21	79.2
MKR	13.94	13.09	23.77	3.58	2.46	3.01	5.59	1.05	2.16	1.71	5.37	3.76	4.18	6.76	1.58	4.62	3.37	76.23
BANKSCN	2.62	2.95	3.6	11.47	6.32	5.69	5.54	2.64	7.39	5.25	9.73	6.8	6.14	6.35	3.49	7.15	6.88	88.53
BANKSFR	1.89	2.1	1.47	5.89	10.82	8.15	8.21	3.3	6.56	8.01	5.12	8.47	7.41	7.4	3.44	4.5	7.25	89.18
BANKSGER	2.03	2.33	1.76	6.01	8.85	12.01	7.94	3.05	6.23	7.26	5.47	7.56	7.32	7.41	3.1	5.01	6.64	87.99
BANKSIT	3.01	3.29	3.03	4.95	8.38	7.46	11.22	2.99	4.72	6.42	5.1	8.04	7.77	9.66	2.79	4.34	6.82	88.78
BANKSJP	1.38	1.99	1.27	4.83	6.85	6.41	5.78	14.98	6.05	6.82	4.3	6.32	6.09	5.93	10.36	4.19	6.43	85.02
BANKSUS	1.8	2.31	2.25	8.62	7.66	6.51	5.69	2.27	12.64	6.38	7.37	6.94	5.93	6.09	3	8.16	6.38	87.36
BANKSUK	1.54	1.76	1.1	5.81	9.23	7.63	7.25	3.3	6.33	12.71	4.7	8	7.28	7.24	3.42	4.29	8.42	87.29
MSCICN	3.01	3.77	4.13	9.64	5.42	5.03	5.61	2.44	6.06	4.23	11.26	6.9	6.8	6.8	3.31	8.37	7.22	88.74
MSCIFR	2.1	2.36	1.77	5.89	7.84	6.53	7.29	2.77	5.43	6.4	6.17	10.12	9.27	8.45	3.52	5.52	8.59	89.88
MSCIGER	2.28	2.73	1.95	5.54	7.09	6.53	7.3	2.85	4.78	6.04	6.31	9.63	10.57	8.66	3.59	5.74	8.41	89.43
MSCIIT	3.27	3.57	3.32	5.29	6.94	6.41	8.89	2.86	4.54	5.83	5.84	8.55	8.42	10.31	3.12	5.03	7.82	89.69
MSCIJP	1.68	2.67	1.75	4.87	5.55	5.22	5.17	10.2	4.75	5.33	5.2	6.91	7.47	6.23	14.04	6.16	6.82	85.96
MSCIUS	3.14	3.79	3.97	8.03	5.15	4.9	5.4	2.08	7.49	4.29	9.36	6.77	6.75	6.71	3.44	11.99	6.74	88.01
MSCIUK	2.1	2.35	1.68	6.34	7.07	5.95	6.49	3.08	5.23	7.05	6.86	9.02	8.5	8.12	3.71	5.79	10.65	89.35
TO	57.63	64.46	58.14	92.04	101.73	92.53	103.53	47.34	82.33	86.12	96.87	112.32	108.87	115.21	55.25	88.04	106.1	1468.51
Inc.Own	79.76	85.26	81.91	103.51	112.55	104.54	114.75	62.32	94.97	98.83	108.13	122.43	119.45	125.52	69.29	100.03	116.75	TCI
NET	-20.24	-14.74	-18.09	3.51	12.55	4.54	14.75	-37.68	-5.03	-1.17	8.13	22.43	19.45	25.52	-30.71	0.03	16.75	86.38
Panel B: Crypto Bubbles																		
LINK	24.33	19.29	15.26	2.5	1.87	3.11	2.34	0.07	3.74	1.51	5.5	3.28	2.93	3.46	0.85	7.17	2.79	75.67
BAT	20.23	25.64	14.98	2.03	1.6	2.91	2.05	0.08	3.91	1.28	5.03	3.29	2.95	3.04	0.94	7.87	2.15	74.36
MKR	17.73	16.48	27.79	2.23	1.85	2.27	2.77	0.75	2.19	0.78	5.03	3.81	3.49	3.75	0.49	6.25	2.35	72.21
BANKSCN	1.88	1.49	1.33	16.76	5.6	6.39	5.38	0.24	10.69	6.63	10.81	5.87	6.72	6.27	0.46	7.63	5.83	83.24
BANKSFR	1.23	1	1.05	5.09	14.8	8.91	11.72	0.33	5.83	8.71	2.92	9.73	9.62	9.88	0.59	2.47	6.11	85.2
BANKSGER	2.18	1.94	1.41	6.45	9.8	16.79	9.36	0.11	7.3	8.38	3.47	7.18	8.16	7.77	0.75	3.13	5.81	83.21
BANKSIT	1.45	1.19	1.48	4.76	11.38	8.25	14.47	0.31	4.98	8.47	2.67	9.56	9.81	11.88	0.23	2.13	6.97	85.53
BANKSJP	0.92	0.62	0.53	7.07	6.43	5.87	6.03	20.63	7.67	7.79	4.09	5.19	5.5	5.55	7.36	2.48	6.28	79.37
BANKSUS	2.64	2.62	1.47	9.85	5.95	6.85	5.35	0.45	15.82	6.1	7.66	6.59	6.76	5.93	0.94	9.94	5.08	84.18
BANKSUK	0.97	0.75	0.34	6.27	9.2	7.81	9.03	0.54	6.11	15.49	3.54	8.81	8.76	8.73	1	2.34	10.32	84.51
MSCICN	4.14	3.56	3.26	11.52	3.32	3.61	3.21	0.35	8.87	3.98	18.52	5.53	5.78	5.57	1.03	12.18	5.58	81.48
MSCIFR	1.98	1.91	2.28	4.75	8.57	5.64	8.53	0.27	5.66	7.47	4.21	12.95	11.47	10.57	0.52	4.59	8.63	87.05
MSCIGER	1.73	1.67	1.89	5.45	8.46	6.47	8.75	0.27	5.88	7.37	4.44	11.43	12.96	10.38	0.47	4.54	7.86	87.04
MSCIIT	1.98	1.64	1.96	5.17	8.75	6.16	10.71	0.34	5.14	7.49	4.2	10.69	10.53	13.04	0.29	3.51	8.4	86.96
MSCIJP	3.76	3.6	3.88	5.18	4.76	4.25	5.03	4.92	6.97	3.62	6.3	7.27	7.29	6.67	13.52	7.79	5.21	86.48
MSCIUS	5.66	5.83	4.42	8.33	2.65	3.4	2.65	0.37	11.74	2.6	12.49	5.56	5.75	4.62	1.38	18.88	3.66	81.12
MSCIUK	2.07	1.63	1.84	5.56	6.42	5.36	7.32	0.19	5.11	10.4	5.1	10.06	9.21	9.69	0.8	3.92	15.3	84.7
TO	70.56	65.22	57.38	92.21	96.62	87.25	100.22	9.58	101.78	92.6	87.47	113.85	114.72	113.77	18.08	87.95	93.03	1402.31
Inc.Own	94.89	90.87	85.17	108.97	111.42	104.04	114.7	30.21	117.6	108.09	106	126.8	127.68	126.81	31.6	106.82	108.33	TCI
NET	-5.11	-9.13	-14.83	8.97	11.42	4.04	14.7	-69.79	17.6	8.09	6	26.8	27.68	26.81	-68.4	6.82	8.33	82.49
Panel C: Russia-Ukraine War																		
LINK	45.3	23.92	17.43	0.96	0.73	0.56	0.83	0.13	0.64	0.66	2.41	1.2	1.24	1.32	0.11	1.74	0.84	54.7
BAT	24.55	45.58	13.83	0.99	1.05	0.33	1.16	0.13	0.72	0.38	2.11	1.47	3.05	1.5	0.34	2.29	0.52	54.42
MKR	18.96	14.69	47.66	1.67	1.35	0.75	1.55	0.38	2.8	0.96	2.09	1.5	1.23	1.54	0.14	2.04	0.71	52.34
BANKSCN	0.47	0.42	0.75	19.61	6.25	6.57	5.91	1.86	11.54	6.15	9.77	6.5	5.21	6.03	1.6	5.38	5.98	80.39
BANKSFR	0.63	0.49	0.6	5.62	17.53	10.62	11.87	0.9	6.61	11.17	3.74	7.69	5.49	8.37	0.41	1.89	6.36	82.47

(*continued on next page*)

Table 2 (*continued*)

	LINK	BAT	MKR	BANKSCN	BANKSFR	BANKSGER	BANKSIT	BANKSJP	BANKSUS	BANKSUK	MSCICN	MSCIFR	MSCIGER	MSCIIT	MSCIJP	MSCIUS	MSCIUK	FROM
Panel A: Covid-19																		
BANKSGER	0.29	0.13	0.31	6.88	12.31	20.51	9.76	1.62	7.91	11.25	4.33	5.07	4.33	6.34	1.19	1.72	6.06	79.49
BANKSIT	0.42	0.47	0.64	5.28	11.8	8.29	17.35	1.07	6.1	8.63	3.68	8.42	6.64	12.19	0.54	2.52	5.98	82.65
BANKSJP	0.46	0.29	0.55	6.69	6.18	5.14	6.4	25.03	8.84	5.55	3.37	3.93	2.79	4.85	13.61	2	4.32	74.97
BANKSUS	0.41	0.35	1.15	12.11	7.61	7.96	7.12	1.74	20.48	8.12	7.36	5.32	3.2	5.35	0.79	5.56	5.35	79.52
BANKSUK	0.29	0.24	0.47	5.92	12.12	10.36	9.41	1.42	7.48	19.24	3.46	6.53	4.85	7.06	0.8	1.41	8.94	80.76
MSCICN	1.15	1.02	0.97	10.67	4.31	4.93	4.12	1.37	7.55	3.73	21.02	7.36	6.12	5.82	1.56	12.48	5.82	78.98
MSCIFR	0.44	0.48	0.57	5.6	7.63	4.57	8.2	1.2	4.36	5.93	5.99	16.59	11.51	11.42	1.69	4.61	9.21	83.41
MSCIGER	0.51	1.05	0.57	5.13	6.36	4.57	7.36	1.1	2.97	5.29	5.53	13.17	19.34	12.62	1.57	4.98	7.88	80.66
MSCIIT	0.48	0.51	0.54	5.13	8.12	5.35	11.7	1.13	4.36	6.38	4.77	11.45	11.06	16.72	0.95	3.64	7.69	83.28
MSCIJP	0.49	0.4	0.42	4.97	3.38	2.6	4.32	13.67	5.95	3.02	6.51	6.49	5.79	5.46	24.95	6.95	4.63	75.05
MSCIUS	1.33	1.73	1.26	8.02	2.84	2.88	3.69	0.94	7.52	1.91	16.53	6.84	6.22	5.57	1.13	27.58	4.02	72.42
MSCIUK	0.41	0.29	0.39	5.7	7.26	6.16	6.98	1.95	4.84	9.3	5.56	10.41	8	8.84	2.23	3.49	18.2	81.8
TO	51.31	46.48	40.45	91.35	99.31	81.63	100.38	30.6	90.19	88.41	87.17	103.34	86.73	104.29	28.65	62.73	84.3	1277.33
Inc.Own	96.61	92.06	88.11	110.95	116.84	102.14	117.72	55.62	110.67	107.65	108.19	119.93	106.08	121.01	53.6	90.31	102.51	TCI
NET	-3.39	-7.94	-11.89	10.95	16.84	2.14	17.72	-44.38	10.67	7.65	8.19	19.93	6.08	21.01	-46.4	-9.69	2.51	75.14
Panel D: Overall Target Sample																		
LINK	22.81	12.14	13.44	3.82	3.72	2.05	4.42	1.5	5.84	2.06	5.2	3.93	3.23	4.02	2.43	8.09	1.3	77.19
BAT	14.61	27.37	13.07	3.8	2.98	1.33	3.84	1.89	4.05	1.82	5.21	3.24	2.8	3.79	2.47	6.21	1.54	72.63
MKR	11.36	10.43	25.45	4.89	3.39	1.47	4.25	1.77	6.18	2.17	5.6	3.93	3.02	4.16	2.55	7.56	1.82	74.55
BANKSCN	2.41	2.73	3.53	12.48	8.05	5.14	6.6	1.97	9.94	5.23	8.7	7.36	4.95	6.26	2.81	7.05	4.77	87.52
BANKSFR	1.57	2.53	2.16	5.42	13.52	7.54	10.82	1.96	7.55	7.83	4.52	8.24	6.68	8.76	1.72	3.82	5.36	86.48
BANKSGER	1.61	2.37	2.12	5.58	10.93	14.6	9.62	1.62	7.77	8	4.82	6.58	6.26	7.83	1.42	3.77	5.1	85.4
BANKSIT	1.4	2.26	2.31	4.97	11.94	7.87	14.28	1.94	6.17	6.69	4.23	7.91	7.2	10.56	1.48	3.43	5.35	85.72
BANKSJP	2.11	3.15	2.63	5.07	6.2	4.24	5.37	22.26	7.02	5.32	3.92	5.39	4.07	4.24	11.43	2.98	4.59	77.74
BANKSUS	2.2	2.81	3.7	8.46	8.7	6.26	7.28	1.72	14.17	6.5	6.68	6.73	4.93	6.42	2.14	6.9	4.4	85.83
BANKSUK	1.13	2.02	1.68	5.95	11.13	8.47	8.82	1.82	8.21	14.54	4.4	7.08	5.62	7.87	1.43	2.72	7.1	85.46
MSCICN	3.38	3.51	4.9	9.91	5.82	3.76	5.84	1.98	8.58	3.22	12.57	6.93	5.09	6.66	2.69	10.53	4.62	87.43
MSCIFR	1.82	2.6	2.9	6.25	8.68	4.96	8.32	2.08	6.87	5.29	6.43	10.68	8.33	9.58	2.35	6.38	6.48	89.32
MSCIGER	1.38	2.32	1.97	5.37	8.16	5.52	9.05	2.23	5.6	4.96	5.99	9.73	12.04	11.17	2.02	5.54	6.95	87.96
MSCIIT	1.43	2.17	2.08	5.7	9.49	6.21	10.83	1.87	6.25	5.93	5.76	8.95	8.45	12.04	1.62	4.76	6.45	87.96
MSCIJP	2.29	3.02	3.54	5.72	5.83	3.58	5.72	7.98	7.37	3.81	6.67	7.06	5.47	6.3	13.16	8.07	4.4	86.84
MSCIUS	4.39	4.49	5.79	8.08	5.12	2.99	5.23	2.14	9.07	2.67	10.49	7.04	5.37	6.01	3.37	14.33	3.42	85.67
MSCIUK	0.99	1.8	1.83	6.8	8.18	5.6	7.42	2.06	6.68	7.27	6.96	9.43	7.72	9.46	2.04	4.88	10.88	89.12
TO	54.09	60.36	67.64	95.81	118.33	77.01	113.42	36.52	113.14	78.77	95.57	109.52	89.21	113.1	43.97	92.7	73.66	1432.82
Inc.Own	76.91	87.73	93.09	108.29	131.84	91.6	127.7	58.79	127.31	93.31	108.14	120.19	101.25	125.14	57.13	107.03	84.54	TCI
NET	-23.09	-12.27	-6.91	8.29	31.84	-8.4	27.7	-41.21	27.31	-6.69	8.14	20.19	1.25	25.14	-42.87	7.03	-15.46	84.28

Note: This table presents the estimations of the static returns connectedness between defi, G7 banking and stock indices returns for full sample ((Jan, 19 to Oct, 22), COVID-19 (Jan, 20 to Dec, 20), Crypto market crash (Jan, 21 to Dec, 21) and Russia-Ukraine war (Jan, 22 to Oct, 22).

volatility in Mar 2020 almost reached 95% (Yousaf et al., 2023a). Long-term volatility hit an all-time high of 88%, based on the conclusion of the year 2020. However, the invasion of the cryptocurrency bubble in 2021 did not further increase the degree of return overflow. The spillover impact decreased to 77% by May 2021, and eventually crossed the 81% threshold in Oct 2021, as shown in Fig. 1b. In addition, the spillover impact varies from 81 to 78 percent. However, in the final month of the year, this exceeded 81 percent. Fig. 1c (RU-war) demonstrates that the spillover effect recurs at the beginning of 2022, crossing 87.5 percent and reaching a peak of 88.5 percent in Mar 2022. After that, it continues going up and down until it eventually reaches 86.5 percent towards the close of Oct 2022.

The overall connection between Jan 2020 and Oct 2022, which includes all three crises (COVID-19, the crypto boom, and the RU-War), is shown in Fig. 1d. The spillover effect from COVID news reaches over 92% in the first quarter of 2020. The entire world was under lockdown at that moment. It gradually dropped until the second quarter of 2021, when the Crypto boom phase began, when it reached 86.5%. When the Russian-Ukrainian War began in the first quarter of 2022, the spillover effect was almost 86%. In addition, it varies between 86.5% and 87%. The COVID-19 pandemic was a global event that had a sudden and major influence on economies and securities markets worldwide. This explains why the impact of spillovers was strong in the initial quarter of 2020. As a result of the lockdown measures put in place to stop the virus from spreading, economic activity fell precipitously, which in turn caused stock markets to plummet and volatility to soar. Eventually, when economies started to recover and financial markets stabilized, the spillover impact diminished. The COVID-19 pandemic has had a lasting effect on the world economy, as evidenced by the fact that it was still relatively high compared to historical levels.

The consequences of the above distinct types of crises in the study are depicted in Fig. 1, which is backed by (Deng et al., 2022; Naeem et al., 2022; Sun et al., 2022; Umar et al., 2022a; Zhang et al., 2021). Investors should exercise extreme caution when making investments during the time of crisis due to the limited variety of diversification options and the significant susceptibility of the financial markets, banking sector, and DeFi assets towards such unforeseen events as COVID-19, RU-War, and Crypto Bubble.

4.2. Total dynamic connectedness

Here, we share the results of our empirical research. The dynamic return connectedness computation follows the static connectedness measure estimations (i.e., a mean estimate for the COVID-19, Crypto bubble, and RU-war periods). It should be noted that the discussion will mostly focus on the findings we obtain for net directional and net pairwise connections, particularly for COVID-19, the Crypto bubble, and the RU-war periods. It should be noted that the discussion will mostly focus on the findings we obtain for net directional and net pairwise connections, particularly for COVID-19, the Crypto bubble, and the RU-war periods. Bank indices from BANKSCN, BANKSFR, BANKSGER, BANKSIT, BANKSUK, BANKSUS, BANKSJP, and MSCI stocks from the G7, as mentioned above (MSCICN, MSCIFR, MSCIGER, MSCIIT, MSCIUK, MSCIUS, MSCIJP), are used to highlight the recent dynamic interconnectedness of DeFi assets (LINK, BAT, and MKR).

The overall spillover index matrices of the return and volatility connectivity among the variables mentioned above are listed in Table 2. The three panels are listed in Table 2. The connection during the COVID-19 period, which ran from Jan 2020 to Dec 2020, is reported in Panel 2a. The connectivity between variables during the crypto boom (Jan 2021 to Dec 2021) and the RU-War (Jan 2022 to Oct 2022) is similarly reported in panels 2b and 2c.

The total connectivity index (TCI) in panel A is 86.38%, indicating significant spillovers across the COVID-19 period. All Defi assets (LINK, BAT, MKR), BANKSJP, BANKSUK, BANKSUS, and MSCIJP are net recipients of volatility spillovers from other banks and stock markets during the COVID-19 timeframe, even though all other markets are net transmitters. The largest recipients of volatility spillovers among banks was Japan (-37.68%), followed by Japanese stocks (-30.71%) and LINK (-20.24%), while the biggest transmitters were Italy (25.52%), France (22.43%), and Germany (19.45%). MSCIGER and MSCIIT are the two largest transmitters of volatility in panels B (Crypto bubble) and panel C (RU-war), respectively, while Japan (MSCIJP, BANKSJP) is the largest recipient. This is because Japan's financial market is smaller and less liquid than other markets, making it more susceptible to shocks. Second, capital goods, which are frequently exchanged in international financial markets, are one of Germany's main exports.

However, Japan imports significant capital goods, making it more vulnerable to shocks in international financial markets. In the case of the Russian-Ukraine war, Russia was a key energy supplier to Italy, a popular travel destination for Russian visitors. As a result, the Italian economy is more vulnerable to the economic sanctions placed on Russia and the decline in tourism due to the conflict. Japan can endure market shocks better because its financial system is more robust than that of Italy.

4.3. Net returns dynamic connectedness

We examine the time-varying behavior of the interconnection among DeFi assets, banking sector stocks, and financial market equities to thoroughly grasp the spillovers, particularly during key times. The total net return spillovers shown in Fig. 2a, 2b, and 2c are then used. As can be seen in Fig. 2a (COVID-19), the banking sector and stock markets in Canada, France, Germany, and Italy are consistent net transmitters of spillovers with significant spikes, whereas the banking sectors in Japan, the United Kingdom, and the United States, as well as all three DeFi indices, are consistent net recipients of spillovers at significant levels.

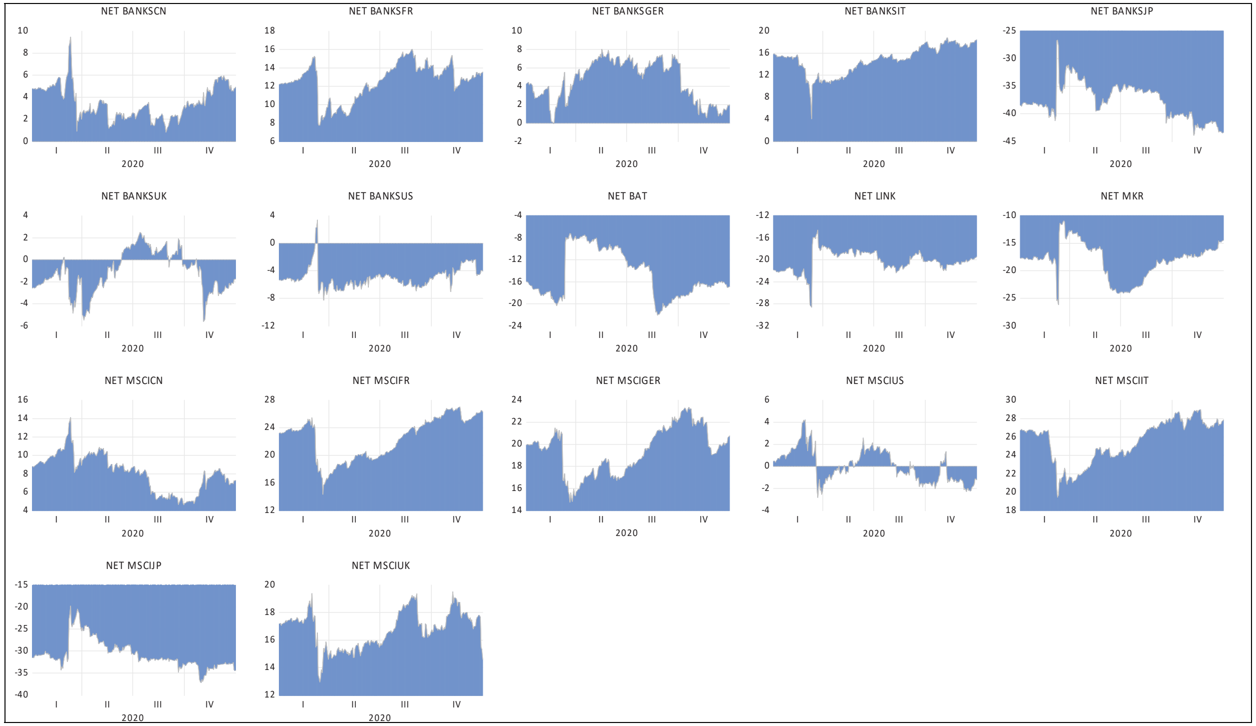

Fig. 2a. This fig presents the basic Net connectedness between defi, G7 banking and stock indices returns for COVID-19 (a=Jan, 20 to Dec, 20).

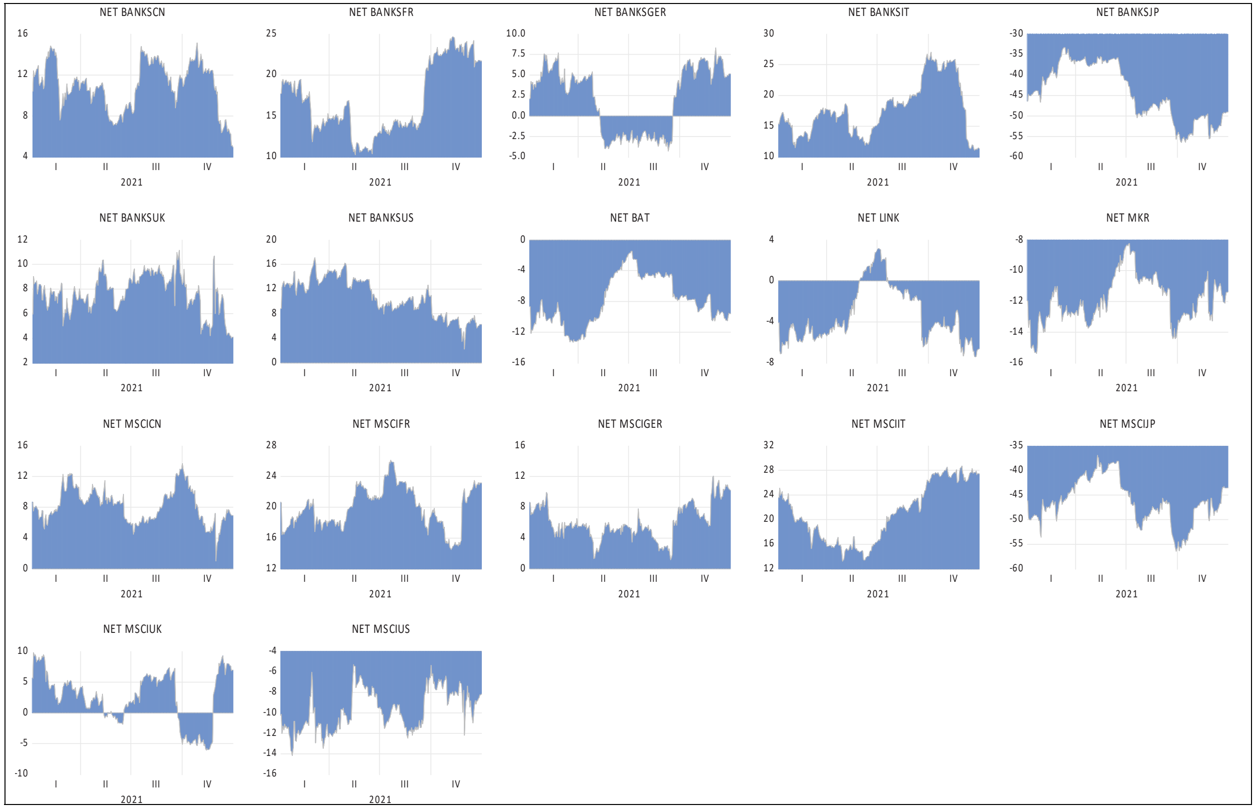

Fig. 2b. This fig presents the basic Net connectedness between defi, G7 banking and stock indices returns for Crypto market crash (b=Jan, 21 to De, 21).

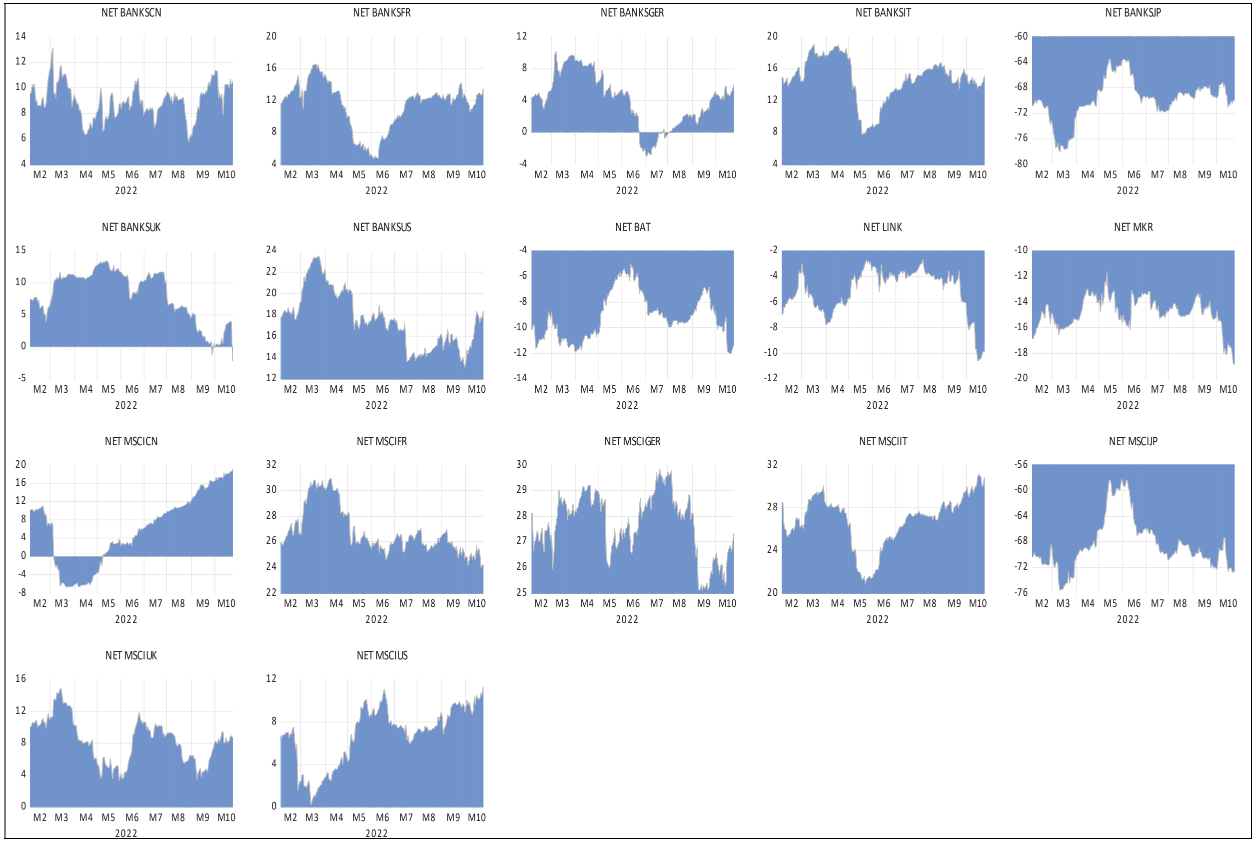

Fig. 2c. This fig presents the basic Net connectedness between defi, G7 banking and stock indices returns for Russia-Ukraine war (c=Jan, 22 to Oct, 22).

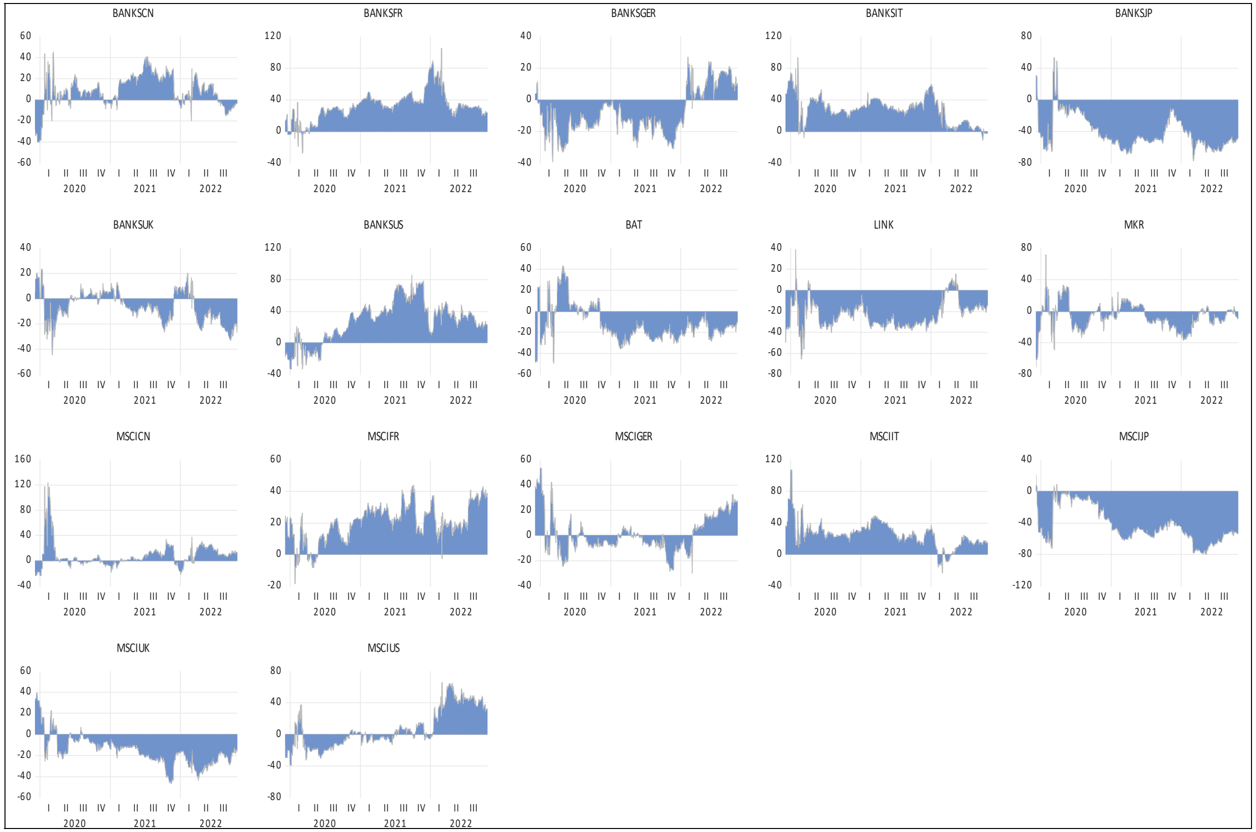

Fig. 2d. This fig presents the basic Net connectedness between defi, G7 banking and stock indices returns for full sample (d=Jan, 19 to Oct, 22).

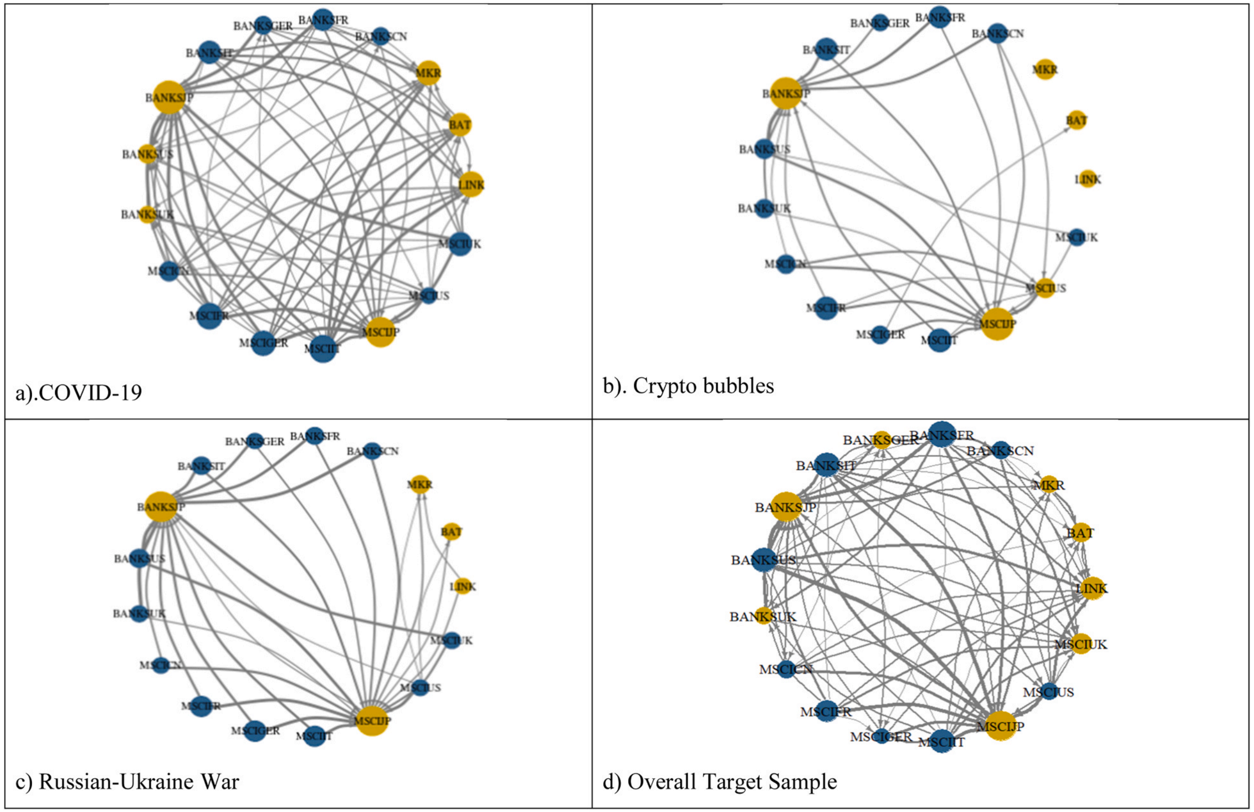

Fig. 3. This fig presents the basic Network connectedness between defi, G7 banking and stock indices returns for COVID-19 (a=Jan, 20 to Dec, 20), Crypto market crash (b=Jan, 21 to Dec, 21), Russia-Ukraine war (c=Jan, 22 to Oct, 22) and full sample (d=Jan, 19 to Oct 22).

Furthermore, as seen in Fig. 2b and 2c, the Japanese banking and securities sectors are consistently net recipients of spillovers, with noticeably high levels during the Crypto boom and RU-War. However, consistent net transmitters of spillovers with discernible peaks are the stock markets and banking indices in Canada, France, Germany, the United States, and Italy.

In all three crises–COVID-19, the Crypto bubble, and the RU-war–which take place concurrently in each of the years from 2020 to 2022, DeFi assets are the primary recipients of spillover. The reason could be that these assets are less liquid than stock markets and are more connected with riskier assets such as cryptocurrency. Second, because the Japanese economy is more export-oriented than the economies of other countries, spillover effects from other countries also affect Japan's banking and stock indices. This makes it more susceptible to alterations in general economic conditions, such as sanctions against Russia by the US and its allies. As a result, spillover effects from foreign markets are more likely to impact the banking and securities sectors in Japan.

According to Fig. 2d (Overall), the Japanese banking sector and the three DeFi indices have consistently been net recipients of spillovers with significant levels. In contrast, the Canadian, French, German, and Italian stock markets and banking sectors have consistently been net transmitters of spillovers with substantial spikes. The results match those displayed in Panels A, B, and C. This indicates that these entities (the Japanese banking sector and Defi assets) have been more impacted by changes in the financial condition in other nations than they have been able to modify that climate themselves.

The finding that DeFi assets are recipients of spillovers from banking and equity markets of G7 nations, except Japan during COVID-19, the crypto bubble, and the RU-War, has been supported by (Uddin et al., 2021; Umar et al., 2022b; Yousaf et al., 2022). This finding should be utilized by global investors, hedgers, or diversifiers to manage their risk exposure and improve their investment performance.

Finally, we create a network graph of the defi-assets LINK, BAT, MKR indices, and MSCICN, MSCIFR, MSCIGER, MSCIIT, MSCIUK, and MSCIJP stock markets to test the robustness of connectivity, as shown in Fig. 3a, b, c. The network graph illustrates how a network of DeFi assets, LINK, BAT, MKR, banks, and stock indices of G7 countries are interconnected in COVID-19, the crypto boom, and the RU war in Fig. 3a, b, and c. Node size is a metric for how interconnected a certain series is to the system as a whole. The node color can determine whether the series is a net shock transmitter (blue) or a receiver (yellow). The blue nodes represent series that transmit shocks to other series, whereas the yellow nodes represent series that receive shocks from other series. The average net pairwise directional connectivity metrics define the size and color of the nodes. These metrics show the strength of a series' correlation with different series and the correlation's directional tendency (i.e., whether the series tends to transmit shocks).

According to the findings in Fig. 3s (COVID-19), all three DeFi assets LINK, BAT, and MKR follow Japanese banks and the stock market as the largest shock receivers. Mild shocks also affect banks in the BANKSUS and BANKSUK. The principal shock transmitters are the stock markets in MSCICN, MSCIFR, MSCIGER, MSCIIT, and MSCIUK; banks in BANKSCN, BANKSFR, BANKSIT, and BANKSGER are also important. The BANKSJP and MSCIJP indices are the primary recipients of shocks from almost every other G7 country, similar to the COVID-19 crisis, as shown in Fig. 3b (Crypto bubble). The DeFi assets LINK, BAT, and MKR do not cause shocks to the BANKSJP and MSCIJP. This demonstrates that DeFi has no impact on the banking or stock markets of G7 nations and that none of these nations' shocks impact DeFi assets, except for Germany.

Further, the banking sector and stock market indicators in Fig. 3c (RU-war) and 3d(overall) are similar to those mentioned above. The main shock transmitters are BANKSCN, BANKSFR, BANKSGER, BANKSUK, BANKSUS, MSCICN, MSCIFR, MSCIGER, MSCIIT, MSCIUK, MSCIUS, and the shock receivers are BANKSJP, MSCIJP, LINK, BAT, and MKR. These findings are consistent with those presented in the tables.

5. Conclusions and implications

Given the new emerging technology, including DeFi problems brought forth by the shocks generated by COVID-19, the crypto bubble, and RUW, investing in DeFi assets is now recognized as a potential asset class for portfolio managers, in addition to banking and stock indicators. However, the risks and challenges of investing in the DeFi business, such as regulatory shifts, market turbulence, technological developments, obsolescence, competition from reputable sectors, and the potential for blockchain technology, worry about stakeholders. To reduce these risks, it is imperative to maintain a diversified portfolio. The main objective of portfolio diversification is to reduce the spillover effects of each asset. Consequently, investors need to understand how a portfolio's assets interact with each other. Given that today's investors mostly rely on technology, and that artificial intelligence is required to eliminate middlemen and centralized institutions from financial transactions, this study highlights the use of DeFi in the construction of banking and stock market portfolios. The goal of this study is to diversify investment portfolios away from financial and banking companies by including DeFi assets. This approach is crucial for guiding fair and long-lasting development in the blockchain industry.

This study investigates volatility spillovers among DeFi assets, banks, and stock indices in G7 nations, focusing on the COVID-19 pandemic, cryptocurrency boom, and Russo-Ukrainian conflict from Jan 2020 to Oct 2022. Using the TVP-VAR model, we analyzed the return spillovers during these interconnected crises. The findings indicate a strong linkage between DeFi assets, banking indices, and stock markets across G7 during these periods, particularly during COVID-19. The banking and equity markets of the G7 countries are the primary sources of volatility spillovers, with Japan and DeFi assets being the most affected. In conclusion, the cryptocurrency boom, Russo-Ukrainian conflict, and COVID-19 had the most pronounced spillover effects in early 2020, coinciding with the onset of the pandemic. While the spillover impact gradually decreased over time, it remained significant compared with the previous periods. Although the Russo-Ukrainian conflict and cryptocurrency boom notably affected financial markets, their global impact was less extensive than that of the COVID-19 pandemic.

Our results contribute to the increasing amount of literature examining the function of DeFi assets in the banking and financial market ecosystems and educating practitioners on smart portfolio management using blockchain technology. The study's findings indicate that DeFi assets do not provide immunity from market volatility and may be more vulnerable to shocks from traditional markets because of their illiquidity, risk, and volatility. These insights can guide improved hedging strategies and portfolio diversification. The analysis reveals that the banking and equity markets of G7, excluding Japan, are more interconnected among themselves than with DeFi assets, highlighting the potential for market shocks to propagate across markets, complicating crisis management.

For effective market oversight, enhancing monitoring across the DeFi, G7 financial institutions, and equity markets is crucial for detecting unusual or manipulative activities. In the case of DeFi disruptions, G7 financial institutions should devise contingency plans for liquidity management and collaborate to address systemic issues. This could also inform the development of early warning systems for systemic risks, allowing investors and portfolio managers to adjust their asset allocation strategies accordingly. This study underscores the importance of diversification across asset classes to mitigate risk, especially given the link between the DeFi and equity markets. It also challenges the assumption of uniformity among market participants, suggesting that analyses must consider the diversity of economic actors. Financial institutions might leverage these insights to innovate and develop new solutions that harness DeFi's advantages, while mitigating its risks. Policymakers' understanding of the correlations between markets during significant events will influence their decisions to implement protective measures against the impacts of market fluctuations in DeFi, G7 banking, and stock markets.

It is worthwhile to discuss the noteworthy ramifications. First, in light of the new crisis results, investors should observe DeFi asset market circumstances in conjunction with the G7 traditional banking and equity markets to promptly and efficiently reallocate their portfolios. Second, stakeholders and investors should exercise caution because global adversities predominantly affect Japanese and DeFi assets. Given these implications, policymakers and regulators should take a proactive stance when drafting laws and promptly update them to address internal and/or external shocks associated with geopolitical risk and keep the shocks from propagating across the market.

It is posited that economic sanctions stemming from the conflict between Ukraine and Russia have a direct and immediate effect on the global market. The scope of this study is limited, as in any other study. Additional aspects, including artificial intelligence, renewable energy, and currency exchange rates, should be considered in future studies. This study only examined G7; more nations and areas might be the subject of further research. A notable constraint of this study is its limited examination of broader international markets and DeFi assets, which restricts a comprehensive understanding of its impact. Consequently, there is a significant opportunity for future research to explore the implications of global DeFi investment opportunities and associated risks for consumers and financial institutions. Although none of these topics are included in the current study, including them in future research may shed additional light on how well the banking industry operates in the twenty-first century. Additionally, it would be intriguing to expand the examination of financial investment to include technological and allocative efficiency in subsequent studies.

CRediT authorship contribution statement

Waqas Hanif: Methodology, Investigation. **Waheed Ullah Shah:** Writing – original draft, Investigation, Formal analysis. **Anna Min DU:** Writing – review & editing, Validation, Supervision, Resources, Conceptualization. **Himani Gupta:** Writing – original draft, Software, Methodology, Investigation, Data curation. **Ijaz Younis:** Writing – original draft, Investigation, Formal analysis, Data curation.

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.

Appendix A

Table 1A
Averaged Returns Connectedness using the forecast horizon of 20-day

	LINK	BAT	MKR	BANKSCN	BANKSFR	BANKSGER	BANKSIT	BANKSJP	BANKSUS	BANKSUK	MSCICN	MSCIFR	MSCIGER	MSCIIT	MSCIJP	MSCIUS	MSCIUK	FROM
LINK	19.33	11.24	12.11	3.92	4.31	2.25	5.21	2.26	6.55	2.8	5.03	4.15	3.93	4.58	2.86	7.91	1.57	80.67
BAT	13.51	25.51	12.59	4.1	3.34	1.48	4.24	2.47	4.55	2.36	5.2	3.32	2.82	3.9	2.88	6.03	1.7	74.49
MKR	9.82	9.95	23.23	5.18	3.84	1.54	4.48	2.59	6.61	2.92	5.39	4.1	3.56	4.38	3.17	7.15	2.08	76.77
BANKSCN	2.61	3.03	4.09	11.86	8.54	4.92	6.93	2.31	9.9	5.59	7.89	7.35	4.79	6.18	2.9	6.65	4.46	88.14
BANKSFR	1.93	3.11	2.93	5.4	13.31	6.84	10.68	2.21	7.67	7.73	4.43	8.08	6.4	8.49	1.91	4	4.88	86.69
BANKSGER	1.89	2.76	2.74	5.64	11.08	13.55	9.42	1.89	7.94	7.99	4.8	6.52	5.97	7.51	1.66	3.86	4.78	86.45
BANKSIT	1.71	2.71	3.1	4.95	12.24	7.38	13.89	2.21	6.33	6.62	4.1	7.81	6.89	9.91	1.71	3.55	4.91	86.11
BANKSJP	3.14	4.53	4.33	5.1	6.45	4.21	5.61	19.06	7.29	5.57	3.95	5.44	3.9	4.08	10.05	2.99	4.31	80.94
BANKSUS	2.55	3.42	4.57	8.06	8.9	5.79	7.56	1.94	13.47	6.61	6.21	6.64	4.87	6.44	2.28	6.6	4.08	86.53
BANKSUK	1.57	2.54	2.62	6.08	11.16	7.99	8.54	1.93	8.48	14.38	4.33	6.95	5.21	7.44	1.58	2.74	6.46	85.62
MSCICN	3.49	3.6	5.38	9.67	6.34	3.62	6.31	2.41	8.61	3.56	11.48	6.86	4.92	6.63	2.84	9.94	4.35	88.52
MSCIFR	1.99	2.92	3.41	6.35	8.88	4.71	8.37	2.48	7.05	5.45	6.24	10.23	7.86	9.21	2.5	6.43	5.91	89.77
MSCIGER	1.58	2.67	2.29	5.4	8.45	5.19	9.22	2.69	5.73	4.94	5.75	9.37	11.61	10.88	2.34	5.49	6.41	88.39
MSCIIT	1.7	2.55	2.58	5.75	9.79	5.92	10.72	2.17	6.56	6.1	5.57	8.68	7.95	11.36	1.86	4.9	5.86	88.64
MSCIJP	2.51	3.34	4.14	5.79	6.36	3.49	6.29	7.17	7.91	4.18	6.57	6.99	5.31	6.42	11.21	8.23	4.08	88.79
MSCIUS	4.19	4.51	5.84	7.92	5.64	2.92	5.74	2.8	8.91	3.07	9.69	6.97	5.5	6.24	3.53	13.17	3.36	86.83
MSCIUK	1.24	2.09	2.38	7	8.41	5.35	7.43	2.29	6.9	7.29	6.87	9.22	7.2	9.13	2.12	4.93	10.14	89.86
TO	55.42	64.97	75.1	96.31	123.74	73.61	116.74	41.81	116.99	82.78	92.03	108.43	87.09	111.42	46.17	91.39	69.2	1453.21
Inc.Own	74.75	90.48	98.33	108.17	137.05	87.16	130.63	60.87	130.46	97.16	103.51	118.66	98.7	122.78	57.39	104.56	79.34	TCI
NET	-25.25	-9.52	-1.67	8.17	37.05	-12.84	30.63	-39.13	30.46	-2.84	3.51	18.66	-1.3	22.78	-42.61	4.56	-20.66	85.48

Note: This table presents robustness the estimations of the static returns connectedness between defi, G7 banking and stock indices return for full sample ((Jan, 19 to Oct, 22)

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