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Tail risk connectedness between DeFi and Islamic assets and their determinants

Mabruk Billah [a], Mohammad Enamul Hoque [b], Sinda Hadhri [c], Hung Xuan Do [d,e,*]

[a] Department of Accounting and Finance, College of Business Administration, Prince Mohammad Bin Fahd University, Al Khobar, Saudi Arabia
[b] BRAC Business School, BRAC University, 66 Mohakhali, Dhaka, 1212, Bangladesh
[c] Institute of Sustainable Business and Organizations, Sciences and Humanities Confluence Research Center- UCLy, ESDES, Lyon, France
[d] School of Economics and Finance, Massey University, Auckland, New Zealand
[e] International School, Vietnam National University, Hanoi, Viet Nam

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ABSTRACT

This study explores tail risk spillover between DeFi and Islamic assets using a time-frequency domain approach. We also conduct sub-sample analyses to account for the diverse impacts of COVID-19 and the Russian-Ukrainian conflict on financial markets. Recognizing the importance of global factors in financial market interdependencies, this research also assesses their impacts on tail risk connections. Empirical findings reveal varying levels of total connectedness among DeFi assets, sukuk markets, and Islamic equity indexes across different time spans, indicating a moderate but fluctuating degree of integration. DeFi assets generally appear disconnected from sukuk and Islamic stock markets over various periods, with the notable exception of a strong and consistent link between SNX in the DeFi sector and sukuk markets (excluding the Indonesian market) over medium- and long-term durations, suggesting that both DeFi and Islamic assets have hedging capabilities. Additionally, the integration between DeFi and Islamic assets is weaker during the COVID-19 era compared to the Russian-Ukrainian conflict period, with changes in the transmission mechanism. Further analysis identifies several potential predictors of tail risk connectedness between DeFi and Islamic assets. Our findings have significant risk management implications for investors and DeFi companies.

1. Introduction

Decentralized finance (DeFi)[1] and Islamic finance are two emerging and revolutionary sectors experiencing significant expansion in the global financial landscape. DeFi encompasses various financial components such as protocols, smart contracts, digital assets, lending systems, and decentralized applications (Schär, 2021; Chen & Bellavitis, 2020; Yousaf and Yarovaya, 2022a; Yousaf and

* Corresponding author. School of Economics and Finance, Massey University, Auckland, New Zealand.
E-mail addresses: sbillah@pmu.edu.sa (M. Billah), iiuc.enam@ymail.com (M. Enamul Hoque), shadhri@univ-catholyon.fr (S. Hadhri), H.Do@massey.ac.nz (H.X. Do).

[1] Pieiro-Chousa et al. (2022) demonstrate that DeFi assets are attractive investments as well as a hedge and a safe haven for stock market volatility. Yousaf and Yarovaya (2022a) support the premise that rational investors should consider incorporating DeFi assets into their existing portfolios. Chowdhury et al. (2023) provide evidence that DeFi exhibits higher efficiency as an asset class in comparison to gold and various other assets. Corbet et al. (2023) empirically suggest DeFi as an asset class. Therefore, the aforementioned occurrence has piqued investors' attention to digital financial markets and digital assets.

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Yarovaya, 2022c; Asl & Jabeur, 2024). These elements facilitate direct connections between clients, bypassing intermediaries like financial institutions to provide various financial services. This innovative financial ecosystem promotes transparency, efficiency, inclusivity, and cross-border transactions for a broader clientele (Yousuf et al., 2023c). Highlighting its remarkable growth, the market capitalization of the total value locked (TVL) in the DeFi ecosystem has surged from over $15 billion in 2020 to more than $94 billion as of July 4, 2024 (DeFil Lama, 2024). DeFi assets also exhibit greater efficiency and generate higher returns (Chowdhury et al., 2023). Similarly, Islamic finance is gaining popularity as an alternative to conventional finance, grounded in Shariah principles of ethical investment and risk-sharing. By 2026, the global Islamic financial sector is expected to be worth $6 trillion (IBSi, 2024).

As these markets continue to expand, their potential integration necessitates an understanding of their interdependencies, particularly during tail events. This knowledge is crucial for investors, legislators, and managers. Despite their fundamental differences, DeFi and Islamic finance share significant conceptual and operational similarities that justify examining their spillover effects. Both DeFi and Islamic finance emphasize disintermediation, financial inclusion, ethical/socially conscious investing, and prioritizing real economic activity (Chowdhury et al., 2023; Billah et al., 2023). Under Shariah law, Islamic finance prohibits elements such as interest (*Riba*), excessive uncertainty (*Gharar*), and participation in certain economic sectors including gambling, firearms, and companies violating ethical standards (Hassan and Lewis, 2007). These limitations resonate with DeFi's focus on openness, decentralized governance, and the democratization of finance by eliminating rent-seeking intermediaries (Chen & Bellavitis, 2020).

By adhering to alternative investment philosophies, both DeFi and Islamic finance may exhibit low correlations and act as hedges or safe havens during crises or upheavals in traditional markets (Masih et al., 2019; Pielór-Chousa et al., 2022). Thus, understanding the dependence and hedging attributes of DeFi and Islamic assets, and detecting tail risk spillover, is essential for developing better risk management strategies. Exposure to tail risk can manifest as the risk of a market crash, potentially reducing overall returns on investments (Agarwal et al., 2017).

Theoretically, the underlying assumption of tail risk connectivity between DeFi and Islamic finance lies in cross-market spillover, integrated markets, and portfolio diversification (see Hoque et al., 2023). Market integration and contagion theories endorse that shocks, volatility, and tail risk can be transmitted across asset classes (Billah et al., 2024). These theories suggest that such spillovers may occur through various channels including capital flows, leverage changes, information spillover, and investor sentiment (Bian et al., 2019; Kyle and Xiong, 2001; Yarovaya et al., 2022). Tail risk in the bottom quantiles of a market's return distribution profoundly affects portfolio performance, systemic risk, and financial stability (Liu, 2017; Park, 2015). Furthermore, as innovative asset classes, DeFi and Islamic finance may hold low correlations, potentially leading to low tail risk connections between them. This has implications for portfolio diversification and downside risk management. Consequently, the risk-return trade-off for investors can be significantly improved by diversifying across asset classes with low connectivity during both normal and bearish market conditions.

With the support of the theoretical framework, one could argue that investors, in their pursuit of diversification and risk mitigation, have a deep cognitive interest in understanding the interdependencies of tail risks across different assets. If individuals hold a portfolio consisting of assets with complex interconnections and significant tail risk, particularly when combined with DeFi/Islamic assets, the risks associated with these assets become inherently non-diversifiable. To optimally incorporate DeFi and Islamic assets within an investment portfolio, it is imperative to strategically diversify the inherent risks associated with these assets. One way to achieve this is by constructing an optimal portfolio that includes assets capable of hedging and diversifying against DeFi and Islamic assets. The process of selecting assets as hedgers in a portfolio is crucial. A common argument is that the selection of various assets should be based on concrete evidence of minimal linkages and high hedging capabilities (Kang et al., 2023). Supporting this, Mensi et al., 2023 showed that sukuk are less integrated with conventional emerging stock markets. Ali, Ijaz, and Yousaf (2023) demonstrated that DeFi and metals are less linked and have low spillovers. Yousaf et al. (2022c) found low dependence between DeFi and major currencies. Hence, as new assets, DeFi and Islamic assets could exhibit lower integration and connectedness with other asset classes as well as with each other. Therefore, we hypothesize that DeFi and Islamic assets may hedge each other's tail risk. Therefore, it is crucial to explore the complex tail risk interconnections between DeFi and Islamic assets to gain a holistic understanding of their intricate relationship and to build investment portfolios that include DeFi and Islamic assets.

Based on past empirical evidence, we propose a hypothesis suggesting a modest level of connectivity among DeFi assets, Islamic stocks, and Sukuks. Additionally, existing literature has not yet explored the interconnectedness of DeFi assets with Islamic stocks and Sukuks. Recognizing this research gap and the hypothesized lower degree of connectedness, our present study examines the spillover of tail risk between DeFi and Islamic assets in the time-frequency connectedness domain, as presented by Chatziantoniou et al. (2021). While previous studies have focused on tail dependence, we argue that understanding left tail dependence is crucial for diversifying asset-specific risk. Therefore, we employ the Conditional Autoregressive Value-at-Risk (CAViaR) model to assess the extent of tail risk in DeFi and Islamic assets between May 31, 2018, to July 7, 2023. These CAViaRs are then integrated into a Time-Varying Parameter Vector Autoregressive (TVP-VAR) framework to investigate the existence of tail risk spillover effects and dependencies (Naeem et al., 2023a, 2023c; Zhu et al., 2020).

An alternative method, the frequency domain quantile VAR, follows the rolling window assumption of Diebold and Yilmaz (2012). However, this approach has several issues, including "arbitrarily determined rolling-window size," "loss of data," and "outlier-sensitive parameters." Therefore, integrating CAViaRs with Frequency TVP-VAR can address these technical problems. Furthermore, past studies have shown that global uncertainty, events like COVID-19, the Russia-Ukraine war, and other extreme events drive spillover effects between DeFi/Islamic assets and other assets (Alam et al., 2023; Iqbal et al., 2022a; 2022b; Qao et al., 2022; Umar et al., 2022). Motivated by these findings, the current study investigates how interconnectedness evolves during the COVID-19 and Russia-Ukraine war periods. Additionally, several past studies have confirmed that connectedness are influenced global uncertainty factors and market risk factors (see, Billah et al., 2023; Billah et al., 2024; Elsayed et al., 2024; Hoque et al., 2023; Hoque et al., 2024). In line with those, we also explored how global uncertainty influences the connectedness between DeFi assets and Islamic assets.

Our research makes several significant contributions to the field of DeFi assets and Islamic finance. First, as previously mentioned, there is a research gap concerning the comprehensive detection of spillover and connectedness among DeFi and Islamic assets. This paper thoroughly examines and provides evidence of spillover and connectedness between these asset classes, significantly enriching the literature in this area. Second, prior studies have explored the linkage and connectedness between DeFi assets and other asset classes using the QVAR connectedness approach (e.g., Abdullah et al., 2023; Yousaf et al., 2022a; Yousaf et al., 2022c; Yousaf et al., 2023c; Yousaf et al., 2023d). Specifically, Abdullah et al. (2023) focused on extreme dependency between tokens and REITs using QVAR, but they did not consider the frequency domain, which is crucial for capturing investor behavior and hedging implications. Additionally, Yousaf et al. (2023a) explored only time-varying connectedness among travel and tourism tokens, tourism equity, and other assets. Our study, however, focuses on tail risk spillover between DeFi and Islamic assets, utilizing CAViaRs as a proxy for tail risk within the TVP-VAR connectedness framework. This research extends the existing literature on tail risk, a critical concern in investment and portfolio management (Borri, 2019; Fendel and Neumann, 2021; Mensi et al., 2021). Furthermore, our study enhances the understanding of the potential benefits derived from diversification and hedging strategies through combined exposure to DeFi and Islamic assets. The practical implications of this research lie in its ability to assist financial practitioners in designing and managing investment portfolios that incorporate Islamic asset exposure. This has the potential to yield higher returns and mitigate non-idiosyncratic risks within the realm of decentralized finance (DeFi).

The examination of tail risk spillover between various markets can provide policymakers with valuable insights into strategies for promoting and maintaining financial stability. Additionally, we compare the tail risk spillover and dependency structures between DeFi assets and Islamic assets during a sample period marked by the COVID-19 pandemic and the Russia-Ukraine war. Our findings indicate that tail risk spillover and dependency structures have changed in response to these extreme events. Therefore, this study contributes to understanding the hedging and safe-haven potential of Islamic assets when confronted with innovative financial instruments during extreme events.

The paper is organized as follows: Section 2 outlines the methodology employed in this study. Section 3 presents the data and offers a preliminary analysis. Section 4 provides a comprehensive analysis of the empirical findings and a detailed assessment of their implications. Section 5 offers a comprehensive summary and concludes the paper.

2. Related empirical studies

The literature related to the tail risk interconnectedness of DeFi assets and Islamic assets can be categorized into two strands. The first strand pertains to the interconnectedness of DeFi assets with other asset classes. A growing number of studies indicate the existence of spillover effects among DeFi and other assets, including crypto, equity, bonds, gold, and energy (see Corbet et al., 2021; Yousaf and Yarovaya, 2021).

For instance, Yousaf and Yarovaya (2022c) investigated the connectedness and dependence of DeFi assets on major currency returns using TVP-VAR, discovering a lower degree of connectedness between these markets. Yousaf et al. (2022) explored the extreme dependence of renewable energy tokens on WTI oil, Brent oil, and natural gas markets using QVAR, providing evidence of a tail-dependent structure. Karim et al. (2023) examined how extreme risks were transmitted in blockchain marketplaces, finding that the positive spillover impacts of decentralized finance (DeFi) and cryptocurrencies exceeded the negative spillover impacts of non-fungible tokens (NFTs) during periods of median and very low volatility. Yousaf et al. (2023b) examined quantile spillover between insurance stocks and insurance tokens, finding evidence of a modest level of interdependence between these two markets. Abdullah et al. (2023) delved into the extreme interconnectedness among real estate tokens, REITs, and other assets, discovering evidence of tail-dependent asymmetric connectivity and a global uncertainty factor that amplifies connectedness during adverse market conditions. Yousaf et al. (2023d) also scrutinized market state-dependent spillovers among Meme assets and other asset classes, emphasizing Meme asset information and price drivers, which may impact other asset classes. Similarly, Yousaf et al. (202e) investigated the interconnectedness between healthcare tokens and healthcare stocks, finding that they are not integrated in stable markets but exhibit spillover effects during extreme market conditions and the COVID-19 period. Yousaf et al. (2023a) assessed time-varying interdependence among travel & tourism tokens, tourism equity, and other assets, observing lower connectedness in stable periods but intensified connectedness during crises like COVID-19. Using the same approach, Ali, Ijaz, and Yousaf (2023) found that DeFi and metals markets exhibit weak dependence. Using the TVP-VAR approach, Mensi et al. (2024a) found a higher level of interdependence among DeFi and leading cryptocurrency markets, with long-run connectedness dominating. They also found that connectedness further increased during COVID-19 and the Ukraine-Russia tensions. Mensi et al. (2024b) found extreme interdependence among NFTs and leading cryptocurrencies. Liao et al. (2024) identified tail dependency between traditional finance and DeFi assets, where causality is bi-directional. Younis et al. (2024) provided evidence of connectivity among DeFi, G7 banking, and equity markets, noting that their interdependency increases during crisis periods.

The second strand of literature pertains to the dependence between Islamic assets and innovative assets. For example, Karim and Naeem (2022a), and Karim and Naeem (2022b) found that Islamic financial markets exhibit connectedness with conventional financial markets, where Islamic equities are net transmitters and Sukuk are net recipients of spillovers. Ali, Ijaz, and Yousaf (2023) identified a significant positive association between conventional and Islamic cryptocurrencies. Karim et al. (2023) provided evidence that Islamic markets can mitigate tail-dependent risk in Bitcoin and offer strong diversification and hedging benefits. Rabbani et al. (2023) employed the CAViaR with TVP-VAR connectedness approach to examine the tail connectedness among Islamic and FinTech markets, finding that short-run spectrum spillover dominates the total spillover. Mezghani et al. (2024) found a weak and negative correlation between Bitcoin and Islamic stock markets. Yousaf et al. (2024) discovered a dynamic relationship between metal markets and Islamic cryptocurrencies, noting that volatility spillover is the main influence and long-term effect. They also found that Islamic coins, particularly metals, are recipients of return spillovers and transmitters of volatility spillovers. Past studies have also highlighted that Islamic equity and Sukuk offer diversification, hedging, and safe-haven benefits during extreme market conditions across different asset classes (Bahloul & Mathlouthi, 2022; Yarovaya et al., 2021; Kang et al., 2023; Karim & Naeem, 2022a, 2022b; Karim et al., 2023; Naeem et al., 2023b).

Our comprehensive literature review underscores that both DeFi and Islamic markets exhibit connectedness with other markets, especially concerning left tail connectedness. However, the existing studies have not explored the tail connectedness between these two growing markets, which could potentially hedge each other. Additionally, other past studies have revealed that the connectedness of DeFi and Islamic markets with other financial markets changes with global uncertainty events, such as COVID-19, the Russia-Ukraine war, and other extreme events driving spillover effects (Alam et al., 2023; Iqbal et al., 2022a;2022b; Qao et al., 2022; Umar et al., 2022). The specific investigation of connectivity between DeFi assets and Islamic assets in this context has yet to be explored.

3. Data and methodology

Within the realm of Defi assets, there exist several notable options, including LINK-Chainlink, MKR-Maker, and BAT-Basic Attention Token. Additionally, Synthetix-SNX and Bancor-BNT are also included in this category (Ali, Ijaz, & Yousaf, 2023; Yousaf et al., 2023e; Yousaf and Yarovaya, 2022b). Each of these assets serves a unique purpose within the blockchain ecosystem. For example, LINK is a Chainlink token that is utilized to pay network node operators. MKR, on the other hand, serves as the governance token of MakerDAO and Maker Protocol on the Ethereum blockchain. This enables users to issue and manage the DAI stablecoin. Finally, BAT is the native token of the Brave browser, operating under the Ethereum blockchain. It offers users the ability to receive a small amount of compensation for viewing advertisements on various websites (Yousaf et al., 2023e).

We have meticulously collected and analyzed daily data from a range of Defi assets, including Chainlink-LINK, Maker-MKR, BasicAttentionToken-BAT, Synthetix-SNX, and Bancor-BNT. In addition to this, we have conducted a thorough examination of four renowned Sukuk indices: Dow Jones Sukuk, Thompson Reuters BPA Malaysia Sukuk, Indonesia Government Sukuk, and S&P GCC Sukuk Index. Our research has also delved into seven Islamic stock market indices, such as Dow Jones Islamic Asia Pacific (DJIAP), Dow Jones Islamic World Emerging Market (DJIEM), Dow Jones Islamic GCC Market (DJIGCC), Dow Jones Islamic Europe (DJIEU), Dow Jones Islamic World Market (DJIM), Dow Jones Islamic US Market (DJIUS), and Dow Jones Islamic UK (DJIUK) (Billah et., 2024). All of these indices have been closely scrutinized and analyzed over a period of time spanning from May 31, 2018, to July 7, 2023. We carefully choose Defi assets based on their market capitalization and available data spanning at least three years. Our selection process ensures that only highly capitalized Defi assets with reliable historical data make the cut. Additionally, our range of Sukuk indices is highly regarded in the global Islamic investment market. Among our notable indices is the Dow-Jones Sukuk Index (DJSI), which carefully monitors the returns of Sukuk indices issued around the world. In addition, our Thompson Reuters BPA Malaysia Sukuk (Sukuk Malaysia) index showcases Malaysia Ringgit-denominated, long-term investment-graded Islamic bonds that investors highly value.[2] The Indonesia Government Sukuk (IGSIX) is also a series of Indonesian Sukuk index obtained from IBPA Bond Indices, providing investors with diversified investment opportunities.[3] Lastly, our S&P GCC Sukuk (Sukuk GCC) index is designed to measure the performance of U.S. dollar-denominated, investment-grade sukuk from Gulf Cooperation Council (GCC) countries, offering investors a comprehensive view of the market (Billah et al., 2024). Data on Defi assets are sourced from coinmarketcap.com and sukuk and Islamic equity indices data are sourced from Bloomberg.

We calculate the first-logarithmic differences of the tail risk, representing the shifts in expected uncertainty. As shown in Table 1, the means of these tail risk changes are positive for DJIEM, DJIE, DJIUS, DJIUK, SUKUK Indonesia, LINK, MKR, and SNX, and negative for DJIM, DJIA, DJIGCC, DJSI, SUKUK Malaysia, SUKUK GCC, BAT and BNT. These mixed results are an indication of the performance of used assets during the retained sample period. Additionally, all series exhibit significant positive skewness, leptokurtosis, and non-normal distribution at the 1% significance level as indicated by the Jarque Bera test results. It's noteworthy that all series are deemed stationary at the 1% significance level based on the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) unit-root tests, confirming the fulfillment of prerequisites for estimating a TVP-VAR model.

3.1. Empirical methods

3.1.1. Conditional Autoregressive Value-at-risk (CAViaR)

Our methodology for estimating Value-at-Risk (VaR) involves utilizing the CAViaR model proposed by Engle and Manganelli (2004), which considers asymmetric effects that may not be captured by other approaches such as the symmetric absolute value or

[2] Malaysia has earned its reputation as one of the most prominent destinations for Sukuk investment in the Muslim world, thanks to its highly active secondary market for Sukuk instruments. This has attracted foreign investors who are keen on tapping into the lucrative opportunities and high returns that are offered by the Islamic financial markets. As a result, Malaysia's Islamic finance industry has experienced significant growth over the years, making it a top destination for Shariah-compliant investments. (Abdulkarim & Tabash, 2020).

[3] To calculate the IGSIX Sukuk index, the IBPA fair market price data is utilized. This index is based on a well-established methodology for index calculation that is widely used across the globe. The index calculation process is carried out with utmost transparency, and regular maintenance efforts are undertaken through a Fact Sheet and a Rebalancing Sheet. If you need more information on this matter, please visit https://www.phei.co.id/en-us/Products-and-Services/Bond-Indexes.

Table 1
Descriptive statistics of DeFi assets, sukuk and Islamic equity markets.

	Mean	Max	Min	SD	Skew	Kurt	JB	ADF	PP
Islamic Equity Markets									
Dow Jones Islamic Emerging Markets (DJIEM)	0.002	0.507	−0.112	0.088	1.178	4.617	457.723***	−15.36***	−15.39***
Dow Jones Islamic World Markets (DJIM)	−0.009	0.434	−0.112	0.090	1.296	5.301	673.646***	−22.28***	−22.07***
Dow Jones Islamic Europe (DJIE)	0.004	0.554	−0.112	0.093	1.298	5.173	643.099***	−8.49***	−16.85***
Dow Jones Islamic Asia Pacific (DJIA)	−0.010	0.373	−0.112	0.083	1.017	3.893	276.827***	−23.23***	−26.32***
Dow jones Islamic GCC markets (DJIGCC)	−0.096	1.055	−0.112	0.127	2.267	11.416	5125.403***	−10.51***	−16.71***
Dow Jones Islamic US (DJIUS)	0.080	0.647	−0.113	0.095	1.440	6.511	1156.713***	−13.90***	−20.49***
Dow jones Islamic UK markets (DJIUK)	0.001	0.512	−0.113	0.094	1.469	5.962	976.317***	−15.94***	−15.65***
Sukuk Markets									
Dow Jones Islamic Sukuk Index (DJSI)	−0.149	0.498	−0.109	0.080	1.424	6.294	1063.666***	−17.85***	−17.82***
Thomson Reuters BPA Malaysia Sukuk Index (SUKUK MALAYSIA)	−0.061	0.652	−0.107	0.098	2.048	9.469	3287.558***	−12.32***	−13.97***
Indonesia Government Sukuk Index (SUKUK INDONESIA)	0.329	2.384	−0.113	0.203	4.584	35.028	62244.470***	−19.72***	−19.73***
S&P Sukuk Index of GCC (SUKUK GCC)	−0.246	0.470	−0.112	0.081	1.326	5.429	725.392***	−19.67***	19.71***
DeFi Assets									
Chainlink (LINK)	0.244	1.451	−0.113	0.101	3.429	36.415	65258.570***	−18.639***	−38.461***
Maker (MKR)	0.025	0.879	−0.113	0.105	2.399	13.596	7588.237***	−18.730***	−19.23***
BasicAttentionToken (BAT)	−0.033	0.670	−0.113	0.099	1.992	9.401	3188.099***	−19.734***	−20.34***
Synthetix (SNX)	0.024	4.182	−0.113	0.142	19.914	570.779	18168705***	−21.695***	−22.67***
Bancor (BNT)	−0.045	0.782	−0.113	0.096	1.915	9.854	3457.333***	−20.56***	−20.67***

Note: The descriptive statistics for DeFi assets, sukuk, and Islamic equity markets in the sample are provided in this table. The abbreviations Max, Min, SD, Skew, Kurt, and JB represent the respective maximum, minimum, standard deviation, skewness, kurtosis, and Jarque-Bera values. An asterisk (***) indicates significance at the 1% level.

indirect GARCH (1,1) models. Specifically, the model assumes that the VaR of a given quantile follows an autoregressive process, which can be expressed mathematically. This approach provides greater flexibility and accuracy in estimating VaR, making it a valuable tool for risk management:

$$f_{a,t}(\beta) = \beta_0 + \beta_1 f_{a,t-1}(\beta) + \beta_2 x_{t-1}^{+} + \beta_3 x_{t-1}^{-} \tag{1}$$

In our model, $f_{a,t}$ represents the VaR at a level (which is 5% in our case) for period t. The model constant is denoted β_0. Lagged VaRs and their weights are represented by β_1 and $f_{a,t-1}(\beta)$, respectively. Effects of positive and negative returns on the VaR are represented by β_2 and β_3, correspondingly.

3.1.2. *TVP-VAR frequency connectedness*

In this particular phase, we employ the CAViaR changes as the foundation for a TVP-VAR-based system that links multiple indices that are associated with Defi assets, sukuk, and Islamic equity indices. Our system grows from the groundwork laid by Chatziantoniou et al. (2021), Baruník and Křehlík (2018), and Antonakakis et al., 2020a. The latter study combined the connectivity approach of Diebold and Yilmaz (2012, 2014) with the TVP-VAR framework of Koop and Korobilis (2014) in order to achieve their goals.

To reveal the inverse correlation between fintech, sukuk, and Islamic equity markets, we use a GFEVD-based correlation method estimated with a generalized TVP-VAR, as developed by Antonakakis et al., 2020a. Specifically, we make use of a TVP-VAR model of order one, which can be represented as follows:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t; \quad \varepsilon_t | F_{t-1} \sim N(0, S_t) \tag{2}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + \nu_t; \quad \nu_t | F_{t-1} \sim N(0, \Xi_t) \tag{3}$$

The variable vector Y_t has dimensions $N \times 1$ and is endogenous. The perturbation term ε_t has dimensions $N \times 1$ and a time-varying variance-covariance matrix S_t with dimensions $N \times N$. The VAR coefficient matrix β_t has dimensions $N \times N$, while the perturbation vector ν_t has dimensions $N^2 \times 1$ and a time-varying variance-covariance matrix Ξ_t with dimensions $N^2 \times N^2$. Lastly, $vec(\beta_t)$ refers to the vectorization of β_t.

To obtain the Generalized Forecast Error Variance Decomposition (GFEVD), the Time-Varying Parameter Vector Autoregression (TVP-VAR) model is transformed into a Vector Moving Average (VMA) representation. This involves expressing.

$Y_t = \sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j}$ (4) where A_{jt} is an $N \times N$ matrix following the ordinary Wald representation theorem. The unscaled GFEVD ($\theta_{ij,t}^{g}(H)$) is consequently defined:

$$\theta_{ij,t}^{g}(H)=\frac{S_{ii,t}^{-1}\sum_{t=1}^{H-1}\left(e_i' A_t S_t e_j\right)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1}\left(e_i A_t S_t A_t' e_i\right)} \tag{5}$$

In order to ensure that the selected variable explains 100% of the variance in the estimated error of variable i, we compute a scaled GFEVD $(\widetilde{\theta}_{ij,t}^{g}(H))$ by using $\sum$ as the variance matrix for the error vector ε, s_{ii} to denote the standard deviation of the error term for the $j-th$ equation, and e_i to represent the selection vector with one for the ith elements and zero otherwise. It is important to note that each row should sum to one in this calculation:

$$\widetilde{\theta}_{ij,t}^{g}(H)=\frac{\theta_{ij,t}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij,t}^{g}(H)} \tag{6}$$

at perspective H, $\sum_{j=1}^{k}\theta_{ij,t}^{g}(H)=1,\sum_{i,j=1}^{k}\widetilde{\theta}_{ij,t}^{g}(H)=k$; $\widetilde{\theta}_{ij,t}^{g}(\mathrm{H})$ measures bidirectional connectivity between index j and index i.

One useful tool in calculating various types of connectedness procedures within the Diebold and Yilmaz (2009) framework is the GFEVD. This tool allows for the measurement of a range of directional connectedness types, including the overall directional connectedness of a variable to all other variables ($C_{\blacksquare\leftarrow i,t}(H)$) in Eq. (7), the overall directional connectedness of all variables to a particular variable ($C_{i\leftarrow\blacksquare,t}(H)$) in Eq. (8), the net total directional connectedness ($C_{i,t}(H)$) in Eq. (9), and the pairwise directional connectedness $(C_{ij,t})$ in formula (10).

$$C_{\blacksquare\leftarrow i,t}(H)=\frac{\sum_{j=1, j\neq i}^{N}\widetilde{\theta}_{ji,t}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ji,t}^{g}(H)}\times 100 \tag{7}$$

$$C_{i\leftarrow\blacksquare,t}(H)=\frac{\sum_{j=1, i\neq j}^{N}\widetilde{\theta}_{ij,t}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ij,t}^{g}(H)}\times 100 \tag{8}$$

$$C_{i,t}(H)=C_{\blacksquare\leftarrow i,t}(H)-C_{i\leftarrow\blacksquare,t}(H) \tag{9}$$

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

If $C_{ij,t}>0$ ($C_{ij,t}<0$), variable i leads variable j, indicating that i impacts j more than it is influenced by j.

The TCI, or Overall Connectedness Index, is a statistical tool that gauges the level of interconnectedness and market risk within a network. Studies carried out in 2021 by Chatziantoniou and Gabauer, 2021, as well as Gabauer alone, have determined that the TCI falls between [0, $\frac{K-1}{K}$] due to the fact that its own variance shares are continuously higher than or equal to cross-variance shares. To obtain a TCI that falls within the [0,1] range, an adjusted TCI is utilized:

$$C_t^{g}(H)=\frac{\sum_{i,j=1, i\neq j}^{K}\widetilde{\theta}_{ij,t}^{g}(H)}{\sum_{i,j=1}^{K}\widetilde{\theta}_{ij,t}^{g}(H)}=\frac{\sum_{i,j=1, i\neq j}^{K}\widetilde{\theta}_{ij,t}^{g}(H)}{K} \tag{11}$$

$$C_t^{g}(H)=\left(\frac{K}{K-1}\right)\frac{\sum_{i,j=1, i\neq j}^{K}\widetilde{\theta}_{ij,t}^{g}(H)}{K} \tag{12}$$

$$C_t^g(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{K} \widetilde{\theta}_{ij,t}^g(H)}{K-1} \quad 0 \leq C_t^g(H) \leq 1. \tag{13}$$

In our previous evaluations, we have only focused on assessing connectedness within the same domain. However, we can now use Stiassny's spooky disintegration technique (1996) to obtain the regularity reaction feature $(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h}\Psi_h$, where $i = \sqrt{-1}$. This allows us to define the spectral thickness of x_t at a specific frequency ω. We achieve this by employing the Fourier Transform on a $TVP-VMA(\infty)$ filtered collection. The expression for this transformation is as follows:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x_{t-h}')e^{-i\omega h} = \Psi(e^{-i\omega h})\sum\nolimits_t \Psi'(e^{+i\omega h}) \tag{14}$$

The regularity GFEVD is a combination of spectral density and GFEVD. In the time domain, we must stabilize it using the following method:

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1}\left|\sum_{h=0}^{\infty}\left(\Psi(\tau)\left(e^{-i\omega h}\right)\Sigma(\tau)\right)_{ij}\right|^2}{\sum_{h=0}^{\infty}(\Psi(e^{-i\omega h})\Sigma(\tau)\Psi(\tau)(e^{i\omega h}))_{ii}} \tag{15}$$

$$\breve{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{k=1}^{N}\theta_{ij}(\omega)} \tag{16}$$

In the field of data analysis, $\theta_{ij}(\omega)$ is a crucial metric that denotes the percentage of the *ith* variable's spectrum at frequency ω, which can be attributed to the *jth* shock. Essentially, this metric represents the level of connectedness between different variables at various frequencies. To gain a more comprehensive understanding of connectedness, we need to consider the short, medium and long-term accumulation of frequencies within a specific range $= (a,b)$ where $a,b \in (-\pi,\pi)$, and $a < b$. By doing so, we can obtain a more accurate and detailed assessment of the level of connectedness between variables across different frequencies:

$$\breve{\theta}_{ij}(d) = \int_a^b \breve{\theta}_{ij}(\omega)d\omega \tag{17}$$

One could potentially conduct an analysis of the connectedness methods employed in Diebold and Yilmaz's works from 2012 to 2014. However, in this particular scenario, the focus would be on frequency connectedness actions that provide insight into overflows occurring within a specific frequency range d:

$$TO_i(d) = \sum_{i=1, i\neq j}^{N} \breve{\theta}_{ji}(d) \tag{18}$$

$$FROM_i(d) = \sum\nolimits_{i=1,i\neq j}^{N} \breve{\theta}_{ij}(d) \tag{19}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{20}$$

$$TCI(d) = N^{-1}\sum\nolimits_{i=1}^{N} TO_i(d) = N^{-1}\sum\nolimits_{i=1}^{N} FROM_i(d) \tag{21}$$

This article uses two frequency bands to demonstrate short- and long-term dynamics: $d_1 = (\pi/5, \pi)$, for 1–5 days, $d_2 = (22, \pi/5]$, for 6–22 days, and $d_3 = (0, \pi/22]$ for 23+ days. The abbreviations $TO_i(d_1)$, $FROM_i(d_1)$, $NET_i(d_1)$, and $TCI(d_1)$ represent short-term directional connectivity, connectedness indexes, directional connectedness TO others, and directional connectedness FROM others, respectively. Medium-term instances d_2 show medium-term connectedness indexes and directional connectedness TO others. Finally, long-term instances d_3 show long-term connectedness indexes and directional connectedness TO others. These data can be used to describe the relationship between frequency-domain data from Barunik and Krehlik (2018) and time-domain observations from Diebold and Yilmaz (2012, 2014):

$$TO_i(H) = \sum\nolimits_d TO_i(d) \tag{22}$$

$$FROM_i(H) = \sum\nolimits_d FROM_i(d) \tag{23}$$

$$NET_i(H) = \sum\nolimits_d NET_i(d) \tag{24}$$

$$TCI(H) = \sum_d TCI(d) \tag{25}$$

3.2. Determinants of total, short, medium, and long-term tail risk spillovers

To determine the causes of spillovers, a second-level analysis was conducted after assessing the amount of irregularity using short, total, and long tail risk spillovers. Our modified version of the conventional gravity model for global trade—asset market returns is used, and we predict that spillovers may be minimal in larger marketplaces. In addition, global influences are considered as additional gravitational factors. It is believed that a variety of variables, including EPU, VIX, OVX, GVZ, EVZ, EMV, GFS, and CLMT,[4] will inevitably affect the impact of shocks on AI-based stocks, tokens and Defi assets at the short, total, and long tail risk spillovers. The pooled OLS regression model, which is based on the fundamental gravity model but has been adjusted to include global index-related variables, is used in this case, considering gravity factors. Balli et al. (2019, 2021) have defined a recognized regression model for AI-based stocks, tokens and Defi assets in recent research papers:

$$TSI_{ij,t} = \alpha_0 + a^{*}X_t + \varepsilon_{it} \tag{26}$$

The $TSI_{ij,t}$ dependent variable is created in four different ways, which include the total, short, medium, and long tail risk spillovers between AI-based stocks, tokens *i* and Defi assets *j*. We obtained the data from DataStream. X_t is a matrix that contains the determinants of return and volatility connectedness, such as $EPU, VIX, OVX, GVZ, EVZ, EMV, GFS, CLMT\ and\ UCRY$. While the independent variables are the same for all combinations of *i and j*, we enlarged their dimensions to perform the pooled OLS. EPU refers to the US economics policy uncertainty, VIX, OVX and GVZ represent the stock markets, oil and gold volatility indices, EVZ is the European currency volatility index, EMV is the equity market volatility index, GFS estimates the global financial stress, CLMT is the MSCI world climate change index, and UCRY is the cryptocurrency price uncertainty index. The Appendix Table provides further details about these variables and others.

In order to assess hedging efficiency (HE), we employ the MCoP technique as suggested by Broadstock et al. (2021). Furthermore, we determine the relative productivity and risk of various products by ranking them based on their Sharpe Ratio.

4. Empirical findings and discussion

We present, in this section, the results of both time- and frequency-domain connectedness among used DeFi assets, sukuks and Islamic equity indices based on a time-varying parameter vector autoregressive approach. We also discuss the findings of the pairwise spillover analysis between underlying markets during the two periods of the COVID-19 pandemic and the Russian-Ukrainian conflict. We also discuss the results of the determinants of total, short, medium and long-term tail risk spillover, as well as the connectedness-based multivariate portfolio analysis.

4.1. Static connectedness analysis between Defi and Islamic assets

We investigate the interconnectivity between the indices of the DeFi and Islamic markets across the entire sample period. The outcomes for the complete dataset are presented in Table 2. It is evident that the spillover within each index is notable, surpassing 38% across all indices. To elaborate, the self-share proportion ranges from 38.36% for the DJIM to 86.51% for Sukuk Indonesia. In terms of the DeFi indices, the most pronounced influences, at 15.25% and 15.07%, are observed between LINK and BNT indices, followed by mutual effects of 12.12% and 10.07% respectively between BNT and MKR. The connectivity among the other pairs is minimal, with spillovers not surpassing 9.82%.

Considering the interactions in relation to Islamic markets, we ascertain that these impacts remain modest, generally not exceeding 2.21%. Specifically, we discern a very low bidirectional influence between DeFi, sukuk and Islamic equity indices.

A comprehensive evaluation of the total spillover from and to individual markets shows that DeFi index BNT holds the strongest information transmission over other indices by 48.87%, while being impacted by them at a rate of 46.79%, establishing itself as a significant net transmitter of shocks. Conversely, apart from LINK, all other DeFi indices emerge as net recipients of shocks in the system, with values of −4.92%, −1.08% and −0.48% for MKR, BAT and SNX, respectively. Amid Islamic markets under scrutiny, DJIM, DJIE, DJIUS, DJIUK, DJSI, and Sukuk GCC emerge as the most substantial net transmitters of shocks within the interconnected system, registering spillover values of 17.22%, 5.39%, 1%, 1.55%, 4.68%, and 4.17%, respectively. The other markets, however, seem to play the role of absorbers of shocks from other markets. Net transmitting role of Islamic markets indicates they could be hedge and safe-haven instruments against tails risk of DeFi indices. At same time, DeFi could be diversifier for tails risk of Islamic asset. Our findings on the role of Islamic asset supported by past studies, who confirmed hedging, and safe-haven benefits during extreme market conditions of different asset classes (see, Bahloul & Mathlouthi, 2022; Yarovaya et al., 2021; Kang et al., 2023; Karim & Naeem, 2022a, 2022b; Karim et al., 2023; Naeem et al., 2023b). On other hand, diversifier role of DeFi in this study is different from Pieiro-Chousa et al. (2022) who found safe haven capacity of DeFi against market volatility.

The static connectedness outcomes also reveal a notable Total Connectedness Index (TCI) of 42.40%, signifying a relatively modest

[4] The variables that we have used in this study, is being used in previous studies, (such as, Batten et al., 2021; Lundgren et al., 2018; Ji et al., 2019; Kocaarslan & Soytas, 2019; Bouri et al., 2021; Saeed et al., 2020, 2021), and these variables are daily basis. Understanding the economic and financial factors that affect the interconnection between Islamic banks and commodities is crucial in making informed investment and risk management decisions. This knowledge enhances investors' awareness and helps them make better decisions. Moreover, to understand the variables further, we have provided the explanations for each variable in Appendix A.1.

Table 2
Averaged spillover index between Defi assets, sukuk and Islamic equity markets.

	DJIEM	DJIM	DJIE	DJIA	DJIGCC	DJIUS	DJIUK	DJSI	Sukuk Malaysia	Sukuk Indonesia	Sukuk GCC	LINK	MKR	BAT	SNX	BNT	FROM
DJIEM	49.17	7.37	4.09	25.83	1.88	3.26	3.4	0.36	1.1	0.77	0.45	0.63	0.5	0.48	0.25	0.46	**50.83**
DJIM	5.52	38.36	9.41	3.97	0.83	30.43	6.67	0.88	0.33	0.51	0.76	0.45	0.25	0.6	0.66	0.38	**61.64**
DJIE	3.38	10.83	43.56	2.26	0.88	5.55	27.48	0.85	0.74	0.99	0.67	0.46	0.55	0.54	0.62	0.63	**56.44**
DJIA	25.22	7.74	3.88	47.91	1.23	4.67	3.64	0.77	0.78	0.72	0.98	0.49	0.46	0.73	0.35	0.43	**52.09**
DJIGCC	3.02	2.58	2.09	1.97	79.86	1.56	1.55	1.15	0.72	0.64	0.96	0.95	0.77	0.68	0.63	0.88	**20.14**
DJIUS	2.57	35.53	5.4	1.78	0.81	44.72	4.27	0.86	0.31	0.58	0.83	0.5	0.35	0.53	0.59	0.37	**55.28**
DJIUK	2.94	7.85	28.87	2.32	0.47	4.4	46.2	1.18	0.64	1.34	1.13	0.38	0.38	0.68	0.65	0.56	**53.8**
DJSI	0.27	0.82	0.67	0.99	0.58	0.75	0.81	50.09	1.69	0.44	37.99	1.33	0.62	0.63	1.82	0.49	**49.91**
Sukuk Malaysia	1.11	0.84	1.34	1.15	0.83	0.62	1.32	4.26	80.85	0.6	2.58	0.86	0.44	0.92	1.64	0.63	**19.15**
Sukuk Indonesia	0.96	0.91	1.34	0.89	0.73	0.8	2.05	0.66	0.54	86.51	0.82	0.55	0.58	1.01	0.81	0.85	**13.49**
Sukuk GCC	0.27	0.58	0.59	0.9	0.59	0.64	0.67	37.51	0.9	0.57	49.49	1.83	0.64	0.8	3.42	0.6	**50.51**
LINK	0.74	0.82	0.6	0.57	0.45	0.93	0.41	1.62	1.05	0.78	2.21	53.75	8.71	7.68	4.44	15.25	**46.25**
MKR	0.5	0.46	0.7	0.41	0.79	0.55	0.51	1.05	0.37	0.46	0.96	10.06	60.82	6.33	3.92	12.12	**39.18**
BAT	0.32	0.71	0.78	0.63	0.36	0.86	0.73	0.93	0.86	0.95	0.98	8.25	5.77	64.1	3.96	9.82	**35.9**
SNX	0.21	0.87	0.91	0.26	0.61	0.53	0.9	1.46	0.86	0.26	2.11	5.06	4.19	4.63	71.76	5.39	**28.24**
BNT	0.57	0.94	1.15	0.55	0.62	0.74	0.94	1.05	0.47	0.75	1.26	15.07	10.07	8.6	4.01	53.21	**46.79**
TO	**47.59**	**78.86**	**61.82**	**44.47**	**11.65**	**56.29**	**55.35**	**54.59**	**11.37**	**10.37**	**54.67**	**46.88**	**34.26**	**34.82**	**27.76**	**48.87**	**42.40**
NET	**−3.23**	**17.22**	**5.39**	**−7.62**	**−8.49**	**1**	**1.55**	**4.68**	**−7.78**	**−3.12**	**4.17**	**0.63**	**−4.92**	**−1.08**	**−0.48**	**2.08**	

Note: The tabular data presented above showcases the spillover effects of Total, net, and pairwise variables in TVP-VAR model. The analysis has been performed using a lag length of order 1, based on Bayesian Information Criterion (BIC), and forecasting has been done for 100 steps in the future.

degree of interdependence and linkages among these examined markets. Remarkably, our analysis indicates that sukuk markets of Malaysia and Indonesia as well as equity index of GCC countries are not very sensitive to external shocks, particularly tail risk of DeFi. This observation is not consistent with prior research that underscores the relatively high levels of integration of these markets with other Islamic markets (e.g., Ahmed & Elsayed, 2019; Aloui et al., 2015; Balcilar et al., 2016; Naeem et al., 2022), but corroborates studies which claim that sukuks carry some risk mitigating features giving the low connectedness with other assets (e.g., Arif et al., 2022; Billah, Nguyen, & Chowdhury, 2023). However, these findings are consistent with Yousaf et al. (2022c) who found low dependence between DeFi and major currencies. Also, they are consistent with our initial hypothesis that being as new assets, DeFi and Islamic assets could exhibit lower integration and connectedness with other asset classes as well as with each other. Our these finding also hints of constructing portfolio with minimal linkages and high hedging capabilities (see, Kang et al., 2023).

Regarding the outcomes pertaining to the 1–5 days timeframe, representing the short-term horizon, the findings (Table 3) exhibit variations in the own-portion spillover, spanning from 30.81% for DJIM to 67.33% for DJIGCC. In the context of the DeFi indices, the most substantial mutual influence is witnessed between LINK and BNT, registering values of 12.40% and 12.36%, respectively. Following closely is the impact between BNT and MKR, which manifests at 9.64% and 8.31% correspondingly. Aside from these noted connections, the spillovers across these indices tend to be very low.

Turning our attention to the interplay between DeFi and Islamic markets, we find results that are qualitatively akin to those observed for the full sample, with feeble spillovers emerging between DeFi, sukuk and Islamic equity indices within the short-term horizon. These spillover effects remain below 1.50% for all pairs. In the realm of net spillover of risk, DJIM, DJIE, DJIUS, Sukuk GCC, LINK and BNT emerge as significant contributors, while MKR and DJIEM take on a prominent role as primary recipients, signifying net spillover values of −3.62% and −3.42%, respectively. The calculated average Total Connectedness Index (TCI) stands at 32.80%, signifying a moderate level of spillover intensity within the overarching system.

Table 4 provides a comprehensive overview of the spillover dynamics within the 5–22 days interval, which characterizes the medium-term scale. The outcomes signify a subdued level of integration during this medium-term horizon, with most cases not surpassing the threshold of 4.93%. Notably, the highest degree of medium-term spillover, in the context of the Defi indices, is observed between BNT and LINK, yielding values of 2.14% and 1.97%, respectively. Similarly, connections with Islamic equity indices and sukuks remain at a low level.

In the spectrum of all series, the extent of spillover transmitted 'TO' other markets varies from 1.69% for DJIGCC to 12.90% for DJIM, implying a moderately significant contribution to risk spillover across all indices. Conversely, the proportions of shocks received 'FROM' other markets are also moderate, spanning from 2.55% for Sukuk Indonesia to 9.82% for DJIM. The Total Connectedness Index (TCI) is calculated at 6.95%, suggesting a relatively weak level of spillover for the medium term across the entirety of the connectedness system.

The results in Table 5 pertain to connectedness over a period of 22 days or more, which is considered long-term. As with the medium-term results in Table 4, there is a low level of spillover for all the indices used, with the highest levels occurring between BNT and LINK at 0.75% and 0.71%, respectively, though still moderate. Regarding the connection of the DeFi indices with Islamic indices, the level of pairwise connectedness is also low and does not exceed 0.23%. The value of TCI within the overall spillover system is about 2.70%. Tables 3–5 show the TCI values indicating the average fluctuations in connectivity among the utilized markets at different time scales. These results suggest that there are time-specific and varying spillover effects between these markets. The upcoming section delves into this dynamic connectedness in further detail.

4.2. Dynamic connectedness analysis between Defi and Islamic assets

In this section, we delve into the examination of dynamic total spillover between the utilized DeFi and Islamic indices, portrayed in Fig. 1, across short- (1–5 days), medium- (5–22), and long-term (>22 days) scales. To achieve this, we employ a dynamic connectedness index based on a first-order Time-Varying Parameter Vector Autoregressive (TVP-VAR) model, incorporating a first-order delay length and a 28-level Generalized Forecast Error Variance Decomposition (GFEVD). This methodology enables us to gauge the evolving spillover patterns, particularly given the significant events within our sample period, such as the Covid-19 pandemic and the Russian – Ukrainian conflict. By encompassing such impactful events, our analysis aims to provide a comprehensive understanding of the dynamic relationship between the studied assets.

Examining the short-term spillovers, we observe a peak of 32 during the early sample period, followed by a subsequent stable phase of less than 30 for the analyzed span till 2020. Notably, an elevated spillover index value coincides with the onset of the Covid-19 period, as it surged to around 40 during the initial stages of the Covid-19 pandemic in early 2020. This heightened interconnectedness aligns with the anticipated dynamics in the aftermath of the Covid-19-induced crisis, which typically triggers increased market uncertainty and interdependence (e.g., Aslam et al., 2020; Guo et al., 2021; Ling et al., 2022). Interestingly, the spillover index experiences a subsequent constancy of around 35 for the remainder of the sample period, potentially implying a hedging effect of these assets during this phase. The effect of the Russian war does not seem to be significant as the spillover index does not exhibit a significant increase during early 2022. This observation aligns with previous studies on the risk-mitigating attributes of DeFi assets during the Covid-19 crisis (Yousaf and Yarovaya, 2022b; Yousaf et al., 2023e).

Looking at the medium and long-term time frames, there is a moderate to low amount of volatility in the total connectedness index throughout most of the analyzed time period. In particular, during the medium-scale timeframe, the total spillover reaches its highest point of 10 in the early stage, but then becomes more stable with a moderately volatile pattern for the remaining period. Although a peak corresponds with the Covid-19 era, they remain relatively modest, not exceeding 10. In the context of the long-term scale, our findings, consistent with those from Table 5, reaffirm the low interdependency across the utilized indices over time. An exception is

Table 3
Averaged spillover index between Defi assets, sukuk and Islamic equity markets at the short term (1–5 Days).

	DJIEM	DJIM	DJIE	DJIA	DJIGCC	DJIUS	DJIUK	DJSI	Sukuk Malaysia	Sukuk Indonesia	Sukuk GCC	LINK	MKR	BAT	SNX	BNT	FROM
DJIEM	41.05	5.73	3.14	21.65	1.59	2.51	2.58	0.29	0.87	0.6	0.4	0.57	0.44	0.38	0.22	0.4	**41.36**
DJIM	4.31	30.81	7.34	2.9	0.67	24.52	4.98	0.58	0.25	0.39	0.5	0.39	0.19	0.4	0.39	0.32	**48.14**
DJIE	2.66	8.35	35.44	1.75	0.72	4.1	21.63	0.64	0.55	0.74	0.52	0.38	0.46	0.44	0.45	0.47	**43.87**
DJIA	20.44	5.31	2.67	39.13	1.03	3.36	2.48	0.52	0.6	0.52	0.7	0.43	0.38	0.49	0.26	0.38	**39.57**
DJIGCC	2.34	1.93	1.58	1.44	67.33	1.16	1.25	0.85	0.61	0.51	0.71	0.77	0.61	0.58	0.46	0.73	**15.53**
DJIUS	1.93	28.82	4.15	1.25	0.64	36.32	3.1	0.65	0.24	0.41	0.65	0.43	0.27	0.39	0.39	0.29	**43.59**
DJIUK	2.3	6.01	23.34	1.84	0.39	3.27	36.88	0.81	0.51	1.02	0.82	0.3	0.31	0.56	0.49	0.42	**42.37**
DJSI	0.21	0.54	0.54	0.64	0.43	0.54	0.64	38.87	1.24	0.35	29.32	1.08	0.47	0.41	0.86	0.35	**37.62**
Sukuk Malaysia	0.86	0.57	0.85	0.83	0.66	0.46	0.83	2.61	60.07	0.38	1.64	0.63	0.3	0.72	0.89	0.44	**12.68**
Sukuk Indonesia	0.73	0.63	0.99	0.63	0.53	0.59	1.46	0.47	0.4	65.57	0.59	0.47	0.51	0.71	0.55	0.68	**9.94**
Sukuk GCC	0.22	0.36	0.51	0.59	0.45	0.47	0.58	28.8	0.6	0.41	38.08	1.5	0.49	0.5	1.33	0.42	**37.23**
LINK	0.63	0.67	0.46	0.47	0.35	0.73	0.3	1.14	0.66	0.54	1.5	42.79	6.72	6.06	3.44	12.36	**36.03**
MKR	0.43	0.33	0.5	0.32	0.59	0.44	0.36	0.82	0.27	0.33	0.68	7.77	48.54	5.12	3.18	9.64	**30.78**
BAT	0.26	0.6	0.61	0.43	0.31	0.77	0.56	0.73	0.61	0.7	0.77	6.42	4.52	50.14	3.24	7.63	**28.16**
SNX	0.15	0.58	0.61	0.18	0.46	0.38	0.6	0.85	0.58	0.18	1.1	3.99	3.18	3.48	42.25	4.14	**20.43**
BNT	0.48	0.73	0.92	0.45	0.51	0.59	0.71	0.88	0.32	0.54	1.09	12.4	8.31	6.88	3.24	42.1	**38.03**
TO	**37.94**	**61.15**	**48.2**	**35.39**	**9.33**	**43.9**	**42.07**	**40.64**	**8.3**	**7.63**	**40.96**	**37.52**	**27.17**	**27.11**	**19.38**	**38.67**	**32.80**
NET	**−3.42**	**13.01**	**4.33**	**−4.18**	**−6.2**	**0.3**	**−0.3**	**3.02**	**−4.37**	**−2.31**	**3.73**	**1.49**	**−3.62**	**−1.05**	**−1.06**	**0.64**	

Note: The tabular data presented above showcases the spillover effects of Total, net, and pairwise variables in TVP-VAR model. The analysis has been performed using a lag length of order 1, based on Bayesian Information Criterion (BIC), and forecasting has been done for 100 steps in the future.

Table 4
Averaged spillover index between Defi assets, sukuk and Islamic equity markets at the medium term (5–22 Days).

	DJIEM	DJIM	DJIE	DJIA	DJIGCC	DJIUS	DJIUK	DJSI	Sukuk Malaysia	Sukuk Indonesia	Sukuk GCC	LINK	MKR	BAT	SNX	BNT	FROM
DJIEM	6	1.2	0.7	3.08	0.21	0.55	0.6	0.05	0.16	0.13	0.04	0.05	0.04	0.07	0.02	0.05	**6.95**
DJIM	0.89	5.52	1.51	0.77	0.12	4.34	1.23	0.2	0.06	0.08	0.17	0.04	0.05	0.14	0.18	0.04	**9.82**
DJIE	0.53	1.81	5.98	0.37	0.12	1.06	4.3	0.15	0.14	0.18	0.11	0.06	0.07	0.07	0.12	0.12	**9.21**
DJIA	3.51	1.77	0.88	6.44	0.15	0.96	0.84	0.17	0.13	0.15	0.19	0.04	0.05	0.17	0.06	0.04	**9.1**
DJIGCC	0.5	0.47	0.38	0.38	9.25	0.29	0.22	0.21	0.08	0.1	0.18	0.13	0.12	0.07	0.12	0.11	**3.35**
DJIUS	0.47	4.93	0.91	0.38	0.12	6.17	0.85	0.15	0.05	0.12	0.13	0.05	0.06	0.1	0.14	0.06	**8.55**
DJIUK	0.47	1.35	4.08	0.35	0.06	0.83	6.85	0.27	0.1	0.24	0.23	0.06	0.06	0.09	0.12	0.1	**8.38**
DJSI	0.05	0.2	0.09	0.25	0.1	0.15	0.13	8.07	0.33	0.07	6.16	0.19	0.1	0.15	0.57	0.09	**8.63**
Sukuk Malaysia	0.18	0.19	0.35	0.22	0.12	0.11	0.36	1.16	15.14	0.15	0.65	0.17	0.1	0.14	0.51	0.13	**4.55**
Sukuk Indonesia	0.17	0.2	0.26	0.18	0.14	0.15	0.42	0.14	0.1	15.28	0.16	0.06	0.05	0.22	0.19	0.13	**2.55**
Sukuk GCC	0.04	0.15	0.06	0.22	0.1	0.12	0.07	6.19	0.21	0.11	8.04	0.24	0.1	0.2	1.21	0.11	**9.12**
LINK	0.08	0.11	0.1	0.07	0.07	0.14	0.08	0.33	0.28	0.17	0.49	8.06	1.45	1.18	0.7	2.14	**7.39**
MKR	0.05	0.09	0.15	0.06	0.14	0.08	0.11	0.17	0.07	0.09	0.19	1.68	9.03	0.89	0.54	1.84	**6.15**
BAT	0.04	0.08	0.12	0.14	0.04	0.07	0.12	0.14	0.18	0.18	0.14	1.34	0.91	10.21	0.52	1.59	**5.6**
SNX	0.04	0.2	0.21	0.05	0.11	0.11	0.21	0.37	0.2	0.05	0.58	0.78	0.74	0.82	18.96	0.89	**5.36**
BNT	0.06	0.16	0.17	0.07	0.08	0.11	0.17	0.13	0.11	0.16	0.12	1.97	1.3	1.26	0.56	8.14	**6.42**
TO	**7.07**	**12.9**	**9.94**	**6.6**	**1.69**	**9.05**	**9.7**	**9.83**	**2.2**	**1.99**	**9.52**	**6.87**	**5.2**	**5.57**	**5.55**	**7.43**	6.95
NET	**0.12**	**3.08**	**0.74**	**−2.5**	**−1.66**	**0.51**	**1.32**	**1.2**	**−2.35**	**−0.57**	**0.41**	**−0.52**	**−0.95**	**−0.04**	**0.19**	**1.01**	

Note: The tabular data presented above showcases the spillover effects of Total, net, and pairwise variables in TVP-VAR model. The analysis has been performed using a lag length of order 1, based on Bayesian Information Criterion (BIC), and forecasting has been done for 100 steps in the future.

Table 5
Averaged spillover index between Defi assets, sukuk and Islamic equity markets at the long term (more than 22 Days).

	DJIEM	DJIM	DJIE	DJIA	DJIGCC	DJIUS	DJIUK	DJSI	Sukuk Malaysia	Sukuk Indonesia	Sukuk GCC	LINK	MKR	BAT	SNX	BNT	FROM
DJIEM	2.13	0.44	0.26	1.11	0.07	0.2	0.22	0.02	0.06	0.05	0.01	0.02	0.01	0.03	0.01	0.02	**2.51**
DJIM	0.32	2.02	0.56	0.29	0.04	1.57	0.46	0.09	0.02	0.03	0.09	0.02	0.02	0.06	0.09	0.02	**3.68**
DJIE	0.19	0.66	2.15	0.14	0.04	0.39	1.56	0.06	0.05	0.07	0.04	0.02	0.02	0.03	0.05	0.04	**3.36**
DJIA	1.26	0.67	0.33	2.34	0.05	0.35	0.31	0.08	0.05	0.06	0.09	0.01	0.02	0.07	0.03	0.02	**3.41**
DJIGCC	0.19	0.18	0.14	0.14	3.27	0.11	0.08	0.09	0.03	0.04	0.07	0.05	0.04	0.03	0.05	0.04	**1.27**
DJIUS	0.18	1.78	0.34	0.15	0.04	2.23	0.32	0.06	0.02	0.05	0.05	0.02	0.02	0.04	0.06	0.03	**3.14**
DJIUK	0.17	0.49	1.46	0.13	0.02	0.31	2.46	0.1	0.04	0.09	0.09	0.02	0.02	0.03	0.04	0.04	**3.05**
DJSI	0.02	0.09	0.03	0.1	0.04	0.06	0.05	3.15	0.13	0.02	2.51	0.07	0.04	0.07	0.39	0.05	**3.67**
Sukuk Malaysia	0.07	0.08	0.14	0.09	0.05	0.05	0.14	0.49	5.65	0.06	0.3	0.06	0.04	0.06	0.24	0.05	**1.92**
Sukuk Indonesia	0.06	0.08	0.1	0.07	0.05	0.06	0.16	0.05	0.04	5.66	0.06	0.02	0.02	0.08	0.08	0.04	**0.99**
Sukuk GCC	0.02	0.07	0.02	0.09	0.04	0.05	0.02	2.52	0.09	0.04	3.38	0.09	0.04	0.1	0.89	0.07	**4.16**
LINK	0.03	0.04	0.04	0.03	0.03	0.05	0.03	0.15	0.12	0.07	0.23	2.89	0.53	0.43	0.3	0.75	**2.83**
MKR	0.02	0.04	0.05	0.03	0.05	0.03	0.04	0.06	0.03	0.04	0.09	0.61	3.25	0.31	0.2	0.65	**2.25**
BAT	0.02	0.03	0.04	0.06	0.02	0.03	0.04	0.06	0.07	0.07	0.07	0.49	0.33	3.75	0.2	0.6	**2.13**
SNX	0.02	0.09	0.09	0.03	0.05	0.05	0.09	0.24	0.09	0.02	0.43	0.29	0.27	0.33	10.55	0.36	**2.45**
BNT	0.02	0.06	0.06	0.03	0.03	0.04	0.06	0.05	0.04	0.06	0.05	0.71	0.46	0.46	0.21	2.98	**2.34**
TO	**2.58**	**4.81**	**3.68**	**2.48**	**0.63**	**3.34**	**3.58**	**4.12**	**0.87**	**0.75**	**4.2**	**2.5**	**1.9**	**2.14**	**2.83**	**2.77**	**2.70**
NET	**0.07**	**1.13**	**0.32**	**−0.94**	**−0.64**	**0.2**	**0.53**	**0.45**	**−1.06**	**−0.24**	**0.03**	**−0.33**	**−0.35**	**0.01**	**0.39**	**0.43**	

Note: The tabular data presented above showcases the spillover effects of Total, net, and pairwise variables in TVP-VAR model. The analysis has been performed using a lag length of order 1, based on Bayesian Information Criterion (BIC), and forecasting has been done for 100 steps in the future.

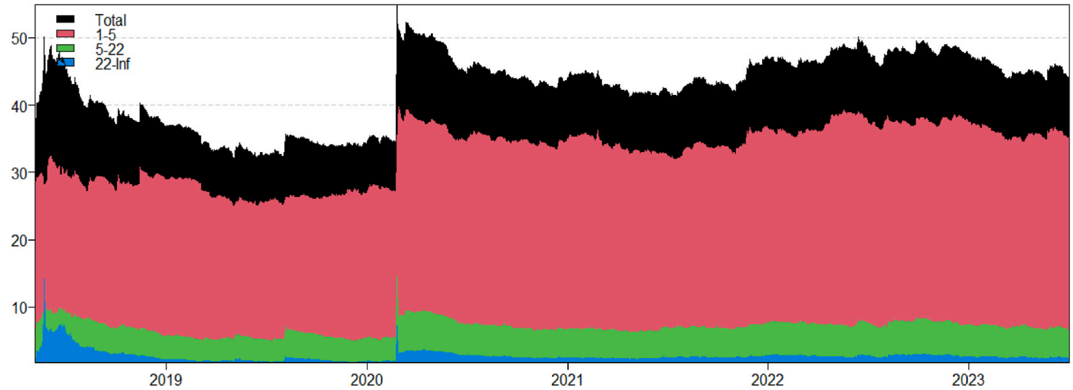
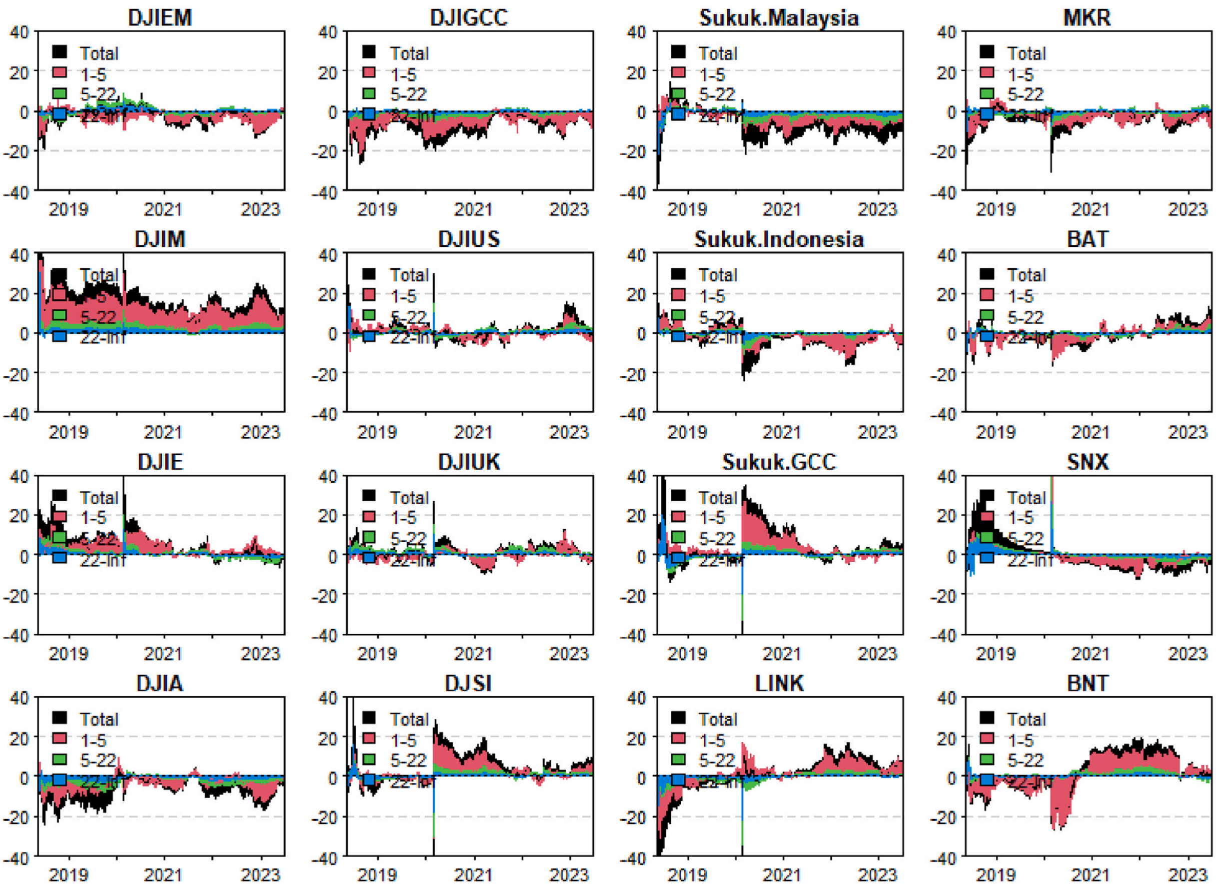


Fig. 1. Total time-varying Tail risk connectedness between Defi assets, sukuk and Islamic equity markets at the total, short (1–5 days), medium (5–22 days) and long-term (more than 22 days). *Notes*: The index for overall dynamic connectedness across the system is derived from a TVP-VAR model with a 1st-order delay length and a 28-level GFEVD.



Note: The graph shown above illustrates the fluctuations in the risk spillovers between Defi assets, sukuk, and Islamic equity markets across various timeframes, including the total, short-term (1-5 days), medium-term (5-22 days), and long-term (more than 22 days).

Fig. 2. Net Directional Connectedness. Note: The graph shown above illustrates the fluctuations in the risk spillovers between Defi assets, sukuk, and Islamic equity markets across various timeframes, including the total, short-term (1–5 days), medium-term (5–22 days), and long-term (more than 22 days).

observed during the early sample period and the Covid-19 outbreak, during which the connectedness index surpasses 10. This outcome implies that shocks stemming from exogenous factors could not significantly influence the dynamic connectedness between DeFi and Islamic assets.

In conclusion, our study uncovers significant albeit moderately fluctuating spillovers across the entire sample period for the employed indices. Crucially, while the nature of these interconnections shifts over time, our results underscore the potential for diversification offered by Islamic and Defi assets, particularly for medium- and long-term investors.

To expand our analysis, we delve into the exploration of time-varying net spillovers. This investigation is visualized through Fig. 2, which presents rolling net spillovers across the temporal domain and across different time frequencies as per short-, medium-, and long-term scales.

The figure unveils a spectrum of connectedness, ranging from low to moderate, with values reaching up to $\pm$ 40. Notably, within the realm of DeFi assets, all indices, except SNX, tend to act as net receivers of shocks during the early sample period (until 2019). Among these, LINK exhibits the highest risk reception degree, recording a value of −40 between 2018 and 2019, while SNX assumes the role of primary net transmitter of shocks, peaking at around 30, during the same period. It's worth highlighting that the decentralized finance (DeFi) was still in its early stages of development during this period. A shift in the spillover dynamics of SNX and LINK emerges from the year 2020 onwards. These indices transition from net receivers to becoming net contributors of shocks, and vice versa. Similarly, BNT and BAT also become net contributors to risk during the late sample period. A plausible explanation for this shift could be attributed to the boarder adoption and expansion of DeFi in the years that follow.

The short-, medium-, and long-term scale figures present similar qualitative outcomes in terms of significant spillover positions across all DeFi indices. Notably, the period between 2020 and 2022 witnesses a more neutral spillover pattern for medium and long-term scales. This observation may suggest that these markets were comparatively less affected by the Covid-19 pandemic that commenced in 2020 and the accompanying slump in asset prices. Generally, the short-term scale results align qualitatively with those of the medium and long-term scales. However, it is worth noting that the short-term scale displays more pronounced peaks in spillover indices, with values exceeding$\pm$20. In contrast to the longer-term scale outcomes, certain alterations are evident, particularly concerning the spillover positions of specific markets in the short-term. Notably, BAT (LINK) exhibits a substantial net spillover receiver (transmitter) role during in 2020, inconsistent across both medium and long-term scales. These outcomes serve to provide further insights to investors.

On the other side, as depicted, Islamic markets seem to display more persistent net spillover positions during the sample period. Specifically, all used equity indices, except DJIGCC assume the role of a net transmitters of shocks across most of the sample period. Considering sukuks, DJSI and Sukuk GCC (Sukuk Malaysia and Indonesia) consistently display a position of a net transmitter (receiver) of shocks after 2020. These insights serve to provide further calibration of the outcomes of Tables 3–5.

4.3. Pairwise spillover during sub-samples

In the preceding section, we delved into the dynamic shifts of individual indices from being net transmitters to becoming net recipients of shocks within the system. Our exploration illuminated alterations in the spillover orientations of certain indices over extended and intermediate timeframes, often aligning with the latter portion of the sample period. Thus, in this section, we endeavor to

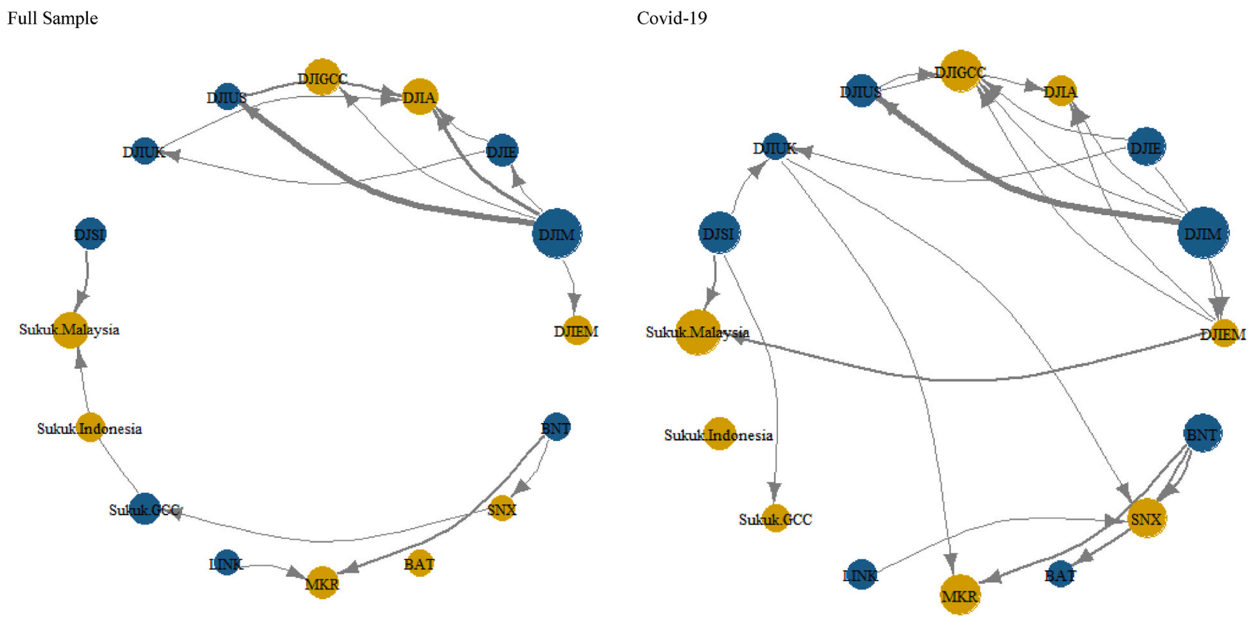


Fig. 3a. Network connectedness.

provide a more comprehensive understanding of both the direction and intensity of these spillovers during the COVID-19 pandemic that commenced in late 2019 and the Russian-Ukrainian war that has begun on February 2022. Illustrating this network of directional spillovers among the indices, Figs. 3 and 4 portray the total (Graph a), short-term (Graph b), medium-term (Graph c), and long-term (Graph d) scenarios during Covid-19 and the Russia-Ukraine war, respectively. For comparison purposes, we also present the results of the full sample.

Initiating with the outcomes of the total spillover for the full sample, our findings unveil that robust pairwise spillover connections are evident from DJIM to DJIUS and DJIA. Additionally, modest yet noteworthy connections are established between all used Islamic equity indices. These outcomes indicate substantial contributions to the system's shocks by most indices, save for DJIGCC, DJIA and DJIEM. Notably, DJIA seems to receive shocks from DJIGCC, DJIM, DJIE and DJIUK, while DJIEM appears to be influenced by shocks from DJIM. For the latter, this influence is relatively minor. This result aligns with prior empirical studies that underscore the relatively low financial integration of emerging markets and corroborates research demonstrating spillovers from world to emerging economies. For sukuks, we note a spillover effect from Sukuk GCC to Malaysian sukuk market that seems to receive shocks also from DJISI. Furthermore, apart from the spillover originated from SNX to sukuk GCC, our results fail to show evidence of any significant connections between used DeFi and Islamic indices.

These patterns hold true for Islamic stock indices when considering the short-term spillover context (days 1–5). Nevertheless, we note that backlinks between used sukuk indices and most of DeFi indices disappear. When considering the medium- and long-term scales, some distinctions emerge. In particular, some robust linkages, not observed in the short-term context, exhibit significance at longer time horizons. Notably, the potent connections endure among Islamic equity markets. Meanwhile, the connections between sukuks as well as DeFi indices exhibit increased potency and become more substantiated. Another noteworthy connection emerges from SNX to sukuk GCC and sukuk Malaysia within the medium- and long-term timeframes.

In summary, results for the full sample serve to confirm and supplement the insights garnered from the net spillover positions showcased in Tables 2–5. The visual representation underscores the enduring connection between Islamic equity markets. Moreover, it highlights the absence of linkages between DeFi and the majority of Islamic bonds and equity indices across the short, medium, and long terms. These insights hold significant utility for investors and fund managers in shaping their portfolio strategies.

Transitioning to the results of the Covid-19 period and the Russian-Ukrainian war, we notice that while certain similarities persist when juxtaposed with the full sample, noteworthy shifts emerge both in terms of net spillover positions and the magnitude of pairwise spillovers.

Commencing with the Covid-19 phase (Fig. 3), outcomes shed light on more pronounced interconnections among the utilized markets. Specifically, more connections are established between Islamic equity markets that manifest heightened susceptibility to external shocks. DJIM, in particular, serves as a focal point for shocks to the majority of Islamic stock indices. Some connections also appear from DJIEM to DJIGCC and Sukuk Malaysia, from DJSI to DJIUK and sukuk GCC, and from DJIUS to DJIGCC. Notable spillovers extend from DJIUK to SNX and MKR, which encounter shocks from other DeFi indices. Within the short-term scale, subdued yet noteworthy connections stretch from DJIEM to Sukuk Malaysia, and from DJIEM to DJIGCC and DJIA. Besides, contrasting the full sample, spillovers among DeFi indices exhibit strength during the Covid-19 period. Furthermore, as for the full sample, links between used Islamic and DeFi indices, showcase no potency throughout this time-scale. Within the medium-term scale, we note a new

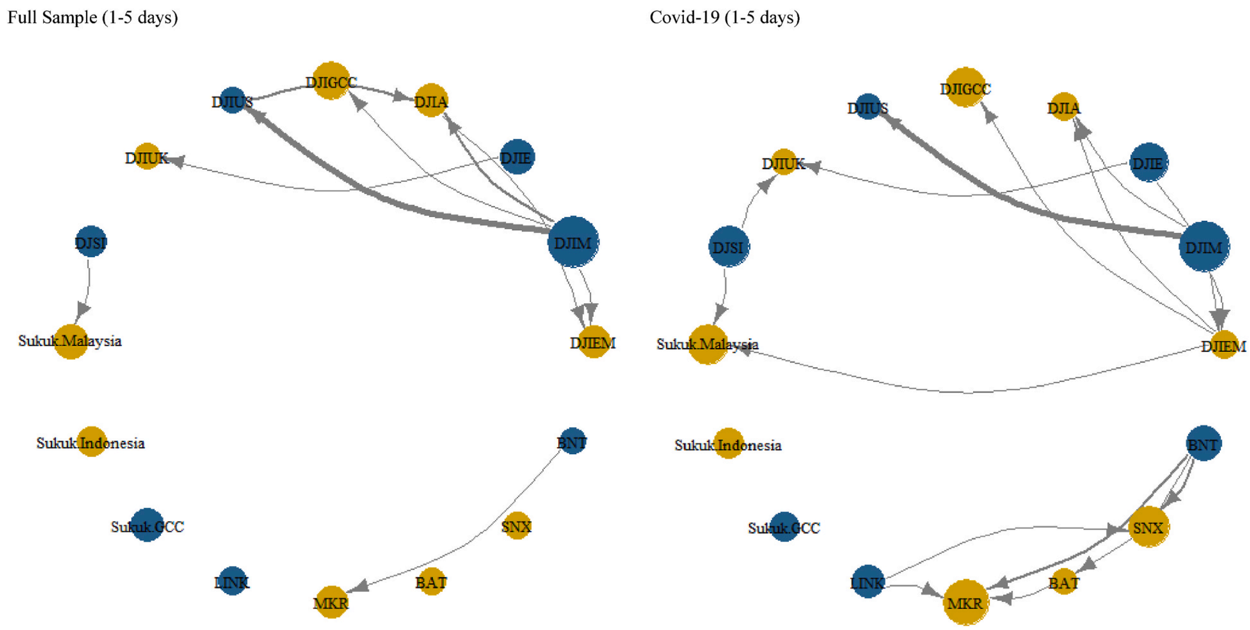


Fig. 3b. Network connectedness.

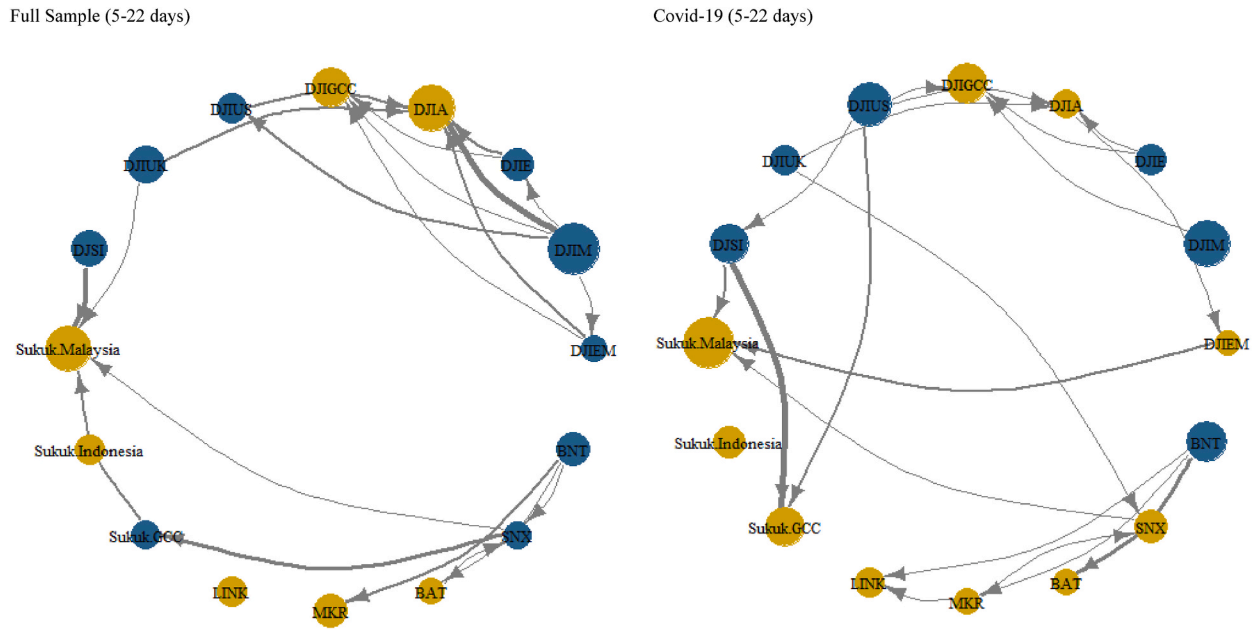


Fig. 3c. Network connectedness.

significant spillover effect from DJIUK to SNX, a maintained connection between SNX and Sukuk Malaysia, and a disappearance of the connection between SNX and Sukuk GCC. Apart from the established linkages, findings propose that investing in DeFi indices is a safe proposition for medium-term Islamic investors during the pandemic. For the long-term scale, results show a reduced resilience of DeFi indices due to their increased connectivities with other Islamic markets. MKR emerges as a risk recipient from DJIM and DJIUK, SNX appears to receive (transmit) risk from (to) DJIUK (Sukuk Malaysia). While the connection between SNX and Sukuk GCC disappears during the pandemic in the long-term horizon, a new established spillover from BAT to DJIM is noticed.

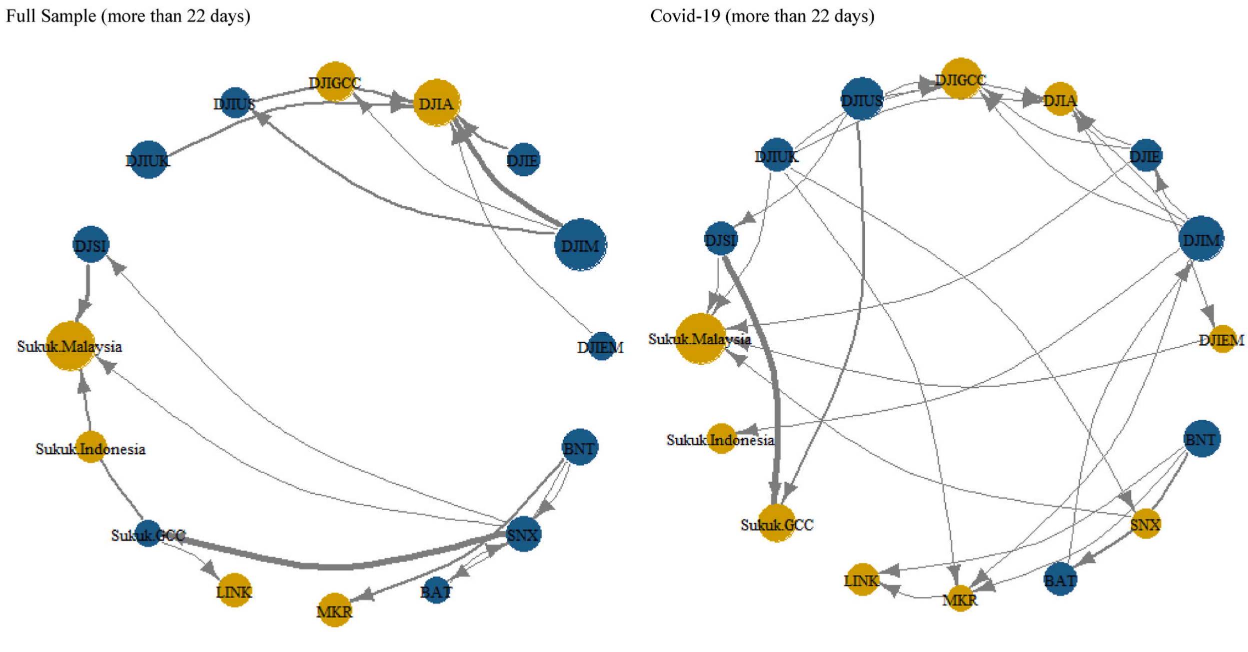
Shifting to the results of the period of the Russian – Ukrainian conflict, a discernible surge in interconnections between DeFi and Islamic bond and equity indices becomes evident compared to the full sample in the three-time horizons. In the short-term context, DJIUK and DJIGCC emerge as net absorbers of shocks from BAT and LINK, respectively, while Sukuk Indonesia absorbs a greater proportion of shocks from BAT and MKR. In the medium-term scale, BAT channel shockwaves towards DJIUK, DJIE and Sukuk Indonesia, whereas LINK and MKR directs their influence towards DJIGCC and Sukuk Indonesia, respectively. The turbulence induced by Russia and Ukraine following the commencement of the conflict between the two countries is discernible in these novel linkages. These perturbations induced a sense of unpredictability in the global stock and bond markets, reverberating into the DeFi markets. Within the long-term context, the enlarged (reduced) prominence of DJIUS (DJIM)'s node signifies an augmented (decreased) magnitude of its impact on shocks within the system, especially other Islamic stock indices. Additionally, apart from the significant link that unfolds from LINK to DJIGCC, the connections between DeFi and Islamic indices display a tendency to wane at the long-term horizon.

Notwithstanding the variations discerned in the sub-samples examined within Figs. 3 and 4, when contrasted with the outcomes of the full-sample analysis, certain conclusions remain robust from an empirical standpoint. Particularly, the recurrent pattern emerges where Sukuk Malaysia, Sukuk Indonesia, DJIGCC and DJIA (alongside DJIM, DJIUS and BNT) consistently manifest their status as net recipients (transmitters) of information irrespective of the time horizon. BNT presents no connections with all the Islamic indices irrespective of the prevailing market circumstances. In a broader context, beyond the specific market interconnections under consideration, the insights unveiled by these figures present captivating prospects for diversification across the short-, medium-, and long-term scenarios.

4.4. Robustness test of TVP-VAR

We performed robust checks of the original TVP-VAR estimation using different alternative forecast horizons such 5, 15, 25, 35 and 45 steps, which is presented in Fig. 5 (Panel A and B). We compare that with Fig. 1. At the first glimpse, we noted that all six TCI have a similar pattern. Additionally, consistent with Fig. 1, we have spotted that Fig. 5a also exhibit similar types of picks and downturn. For example, in early 2018, early 2019, early 2020, and early 2021, there were picks. On other hand, in mid-2019, mid 2020, mid, 2021 and late 2023, there were downturns. These analyses confirm the stability of our initial findings under varying model specifications.

We further estimated models with rolling windows approaches such as DY VAR spillover and QVAR spillover approach, which presented in Fig. 5b. We noted that RW-VAR and RW-VAR exhibit the most similar pattern of spillover changes in comparison to TVP-VAR. Hence, the consistency observed in the findings lends support to the robustness of our main results concerning fluctuations in



Note: An analysis was conducted on a network that shows the connections between Defi assets, sukuk, and Islamic equity markets during the COVID-19 pandemic. The analysis was based on a TVP-VAR model with a first-order delay length and 28-level GFEVD. The size of each variable's contribution to system connectedness was shown in the node dimension, while the color indicated the beginning of connectedness. The node dimension also represented the degree of spillovers impact, and the color defined whether a market was a net transmitter (steer blue) or recipient (gold) of spillovers. The node area was determined using a forced routed design algorithm, and the number of vectors set the node path. Arrowhead size reflected the strength of the pair-wise spillovers, and the color indicated the direction of spillovers from greatest (dark grey) to weakest (grey).

Fig. 3d. Network Connectedness. Note: An analysis was conducted on a network that shows the connections between Defi assets, sukuk, and Islamic equity markets during the COVID-19 pandemic. The analysis was based on a TVP-VAR model with a first-order delay length and 28-level GFEVD. The size of each variable's contribution to system connectedness was shown in the node dimension, while the color indicated the beginning of connectedness. The node dimension also represented the degree of spillovers impact, and the color defined whether a market was a net transmitter (steer blue) or recipient (gold) of spillovers. The node area was determined using a forced routed design algorithm, and the number of vectors set the node path. Arrowhead size reflected the strength of the pair-wise spillovers, and the color indicated the direction of spillovers from greatest (dark grey) to weakest (grey). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

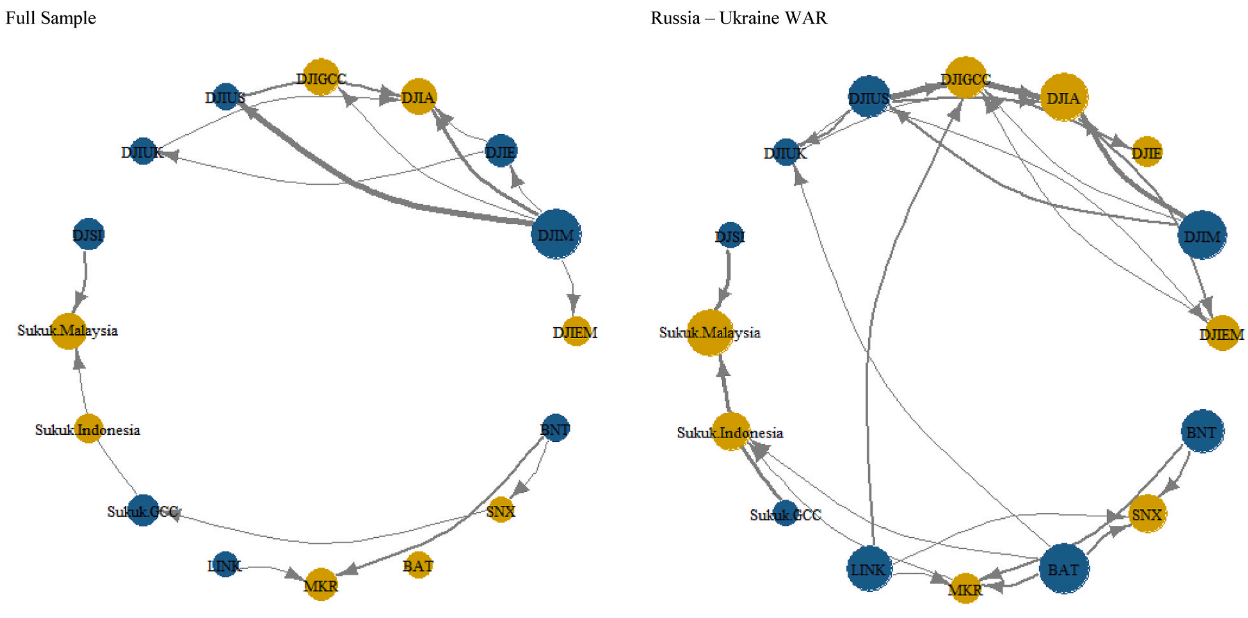


Fig. 4a. Network connectedness.

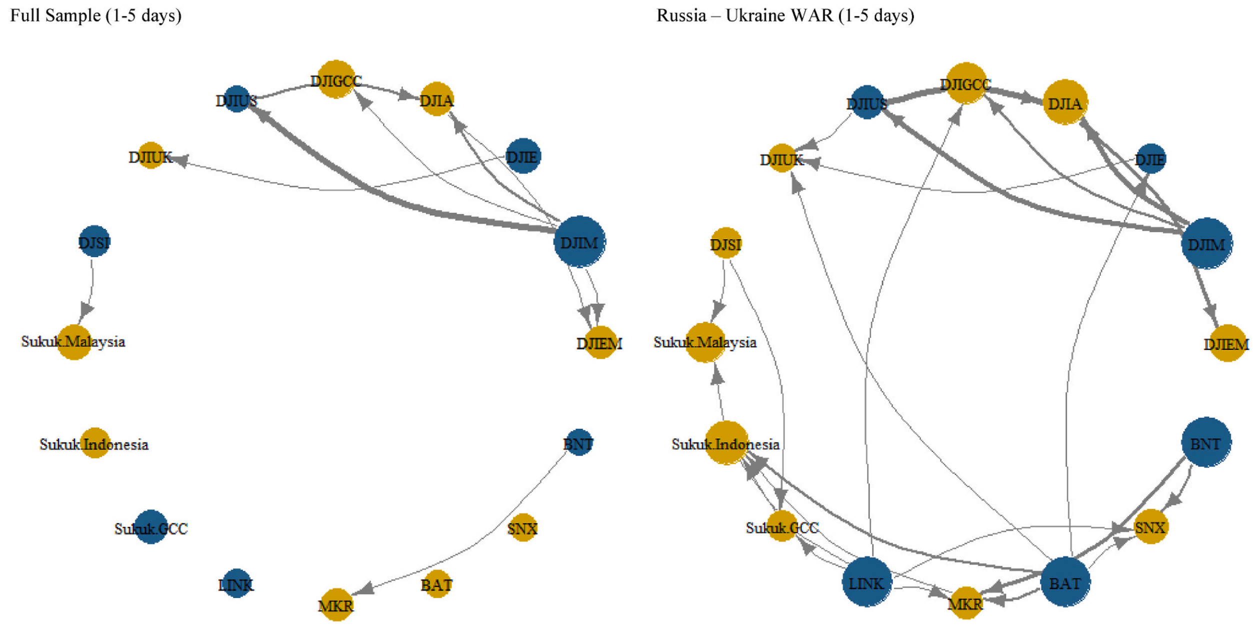


Fig. 4b. Network connectedness.

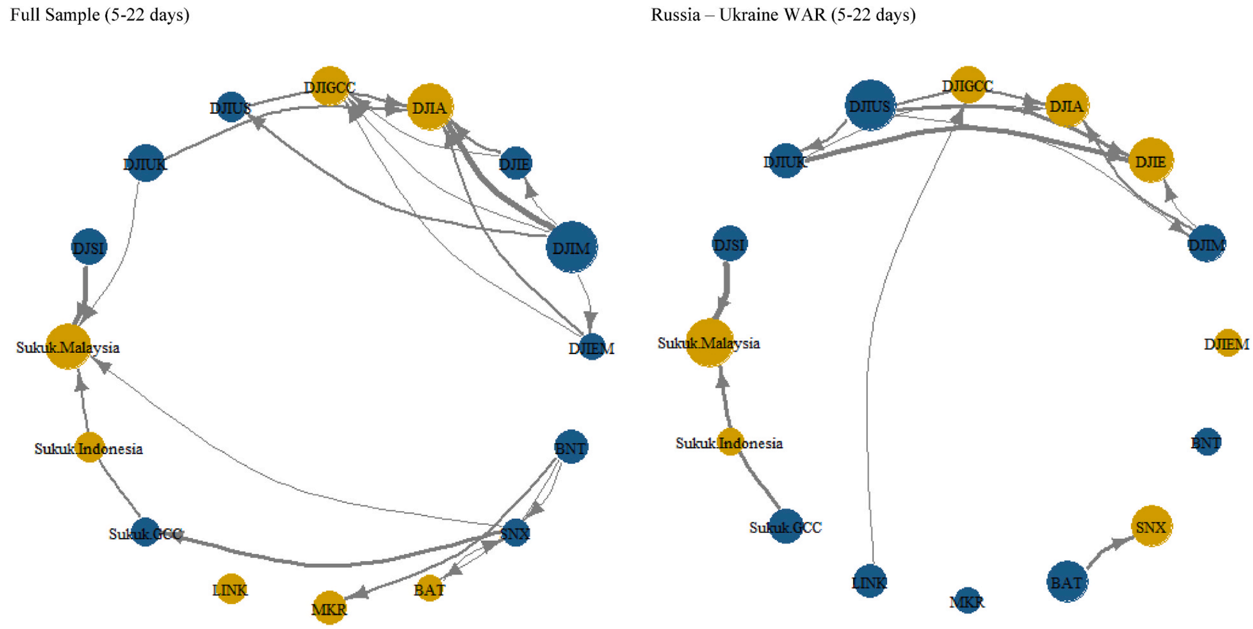


Fig. 4c. Network connectedness.

interconnectedness and spillovers between DeFi and Islamic Assets.

4.5. Determinants of connectedness and spillover

We leverage global risk factors to elucidate this connectedness, and the explanatory variables encompass a range of crucial metrics, namely economic policy uncertainty (EPU), stock market volatility (VIX and EMV), oil market volatility (OVX), gold market volatility (GVZ), global financial stress (GFS), euro/U.S. dollar exchange rate volatility index (EVZ), and the climate change index (CLMT). The particulars of these risk variables are outlined in Table A1 in the appendix. The pairwise correlations amongst these explanatory elements exhibit a moderate range between −0.36 and 0.44, effectively mitigating concerns regarding multicollinearity. These

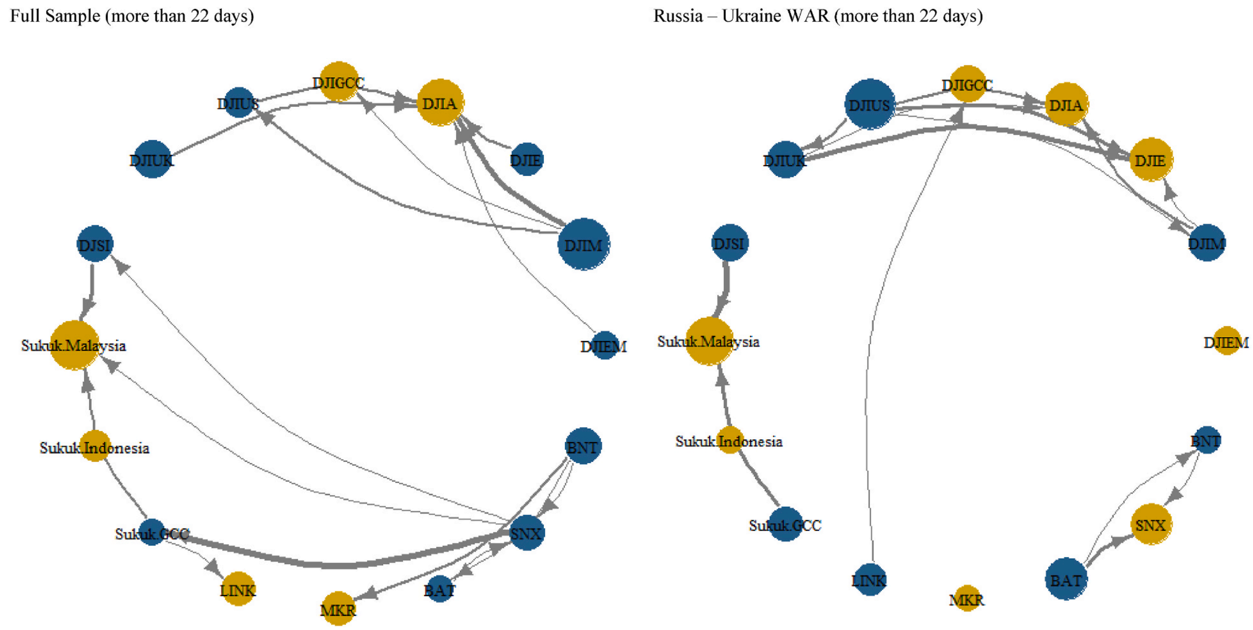


Fig. 4d. Network Connectedness. A complete example of a tail risk connection network between Defi assets, sukuk and Islamic equity markets during Russia – Ukraine WAR at the total, short (1–5 days), medium (5–22 days) and long-term (more than 22 days).

correlation coefficients are presented in Table A2 in the appendix. Moving forward, we have estimated OLS regression considering different types of spillovers, such as Total, Short-, Medium-, and Long-term, as dependent variables and global risk factors as independent variables, which are depicted in Tables 6–9, respectively. These analyses aim to uncover the relationships and interactions between spillovers and these global risk factors in different time frames.

Results in Table 6 for model 1–8, shows that EPU, CLMT has negative effects influence on total connectedness, which VIX, OVX, GVZ, EVZ, GFS, and EMV has positive effects influence on total connectedness. These models capture variation in total connectedness within ranges of 20%–30.20%. Next, when we includes all risk factors into model 9, we find that EPU and OVX exhibit negative influence on total connectedness. It has captured that VIX, EVZ, GFS, and CLMT positive impacts spillover. However, GVZ and EMV found to be insignificant. Additionally, model 9 able to capture 55% variation suggesting a good explanatory power of the used model in predicting total connectedness.

Furthermore, when we look at short connectedness in Tables 7 and in model 1–8, we note that the influence and direction of the risk factors are same those appeared in the total connectedness. Additionally, model 9 exhibits almost similar influence and direction of the risk factors, excluding the effects of GVZ, EVZ, and EMV which turn to be insignificant on short term spillover between DeFi and Islamic assets. The model 9 also captures 47.77% variation. Moreover, for medium connectedness in Table 8, we note that the influence and direction of the risk factors are same those appeared in the total connectedness, across in model 1–8. However, OVX and GFS are insignificant on medium term spillover between DeFi and Islamic assets. Model 9 of Table 8 also captures 57.45%.

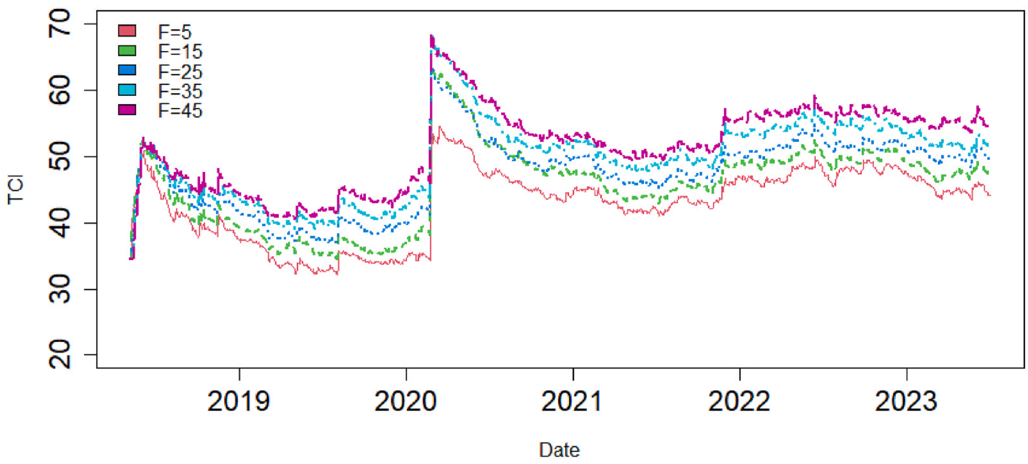
Additionally, for long term connectedness, model 1–8 in Table 9 exhibit a bit different result as VIX, GVZ, and GFS turned to be insignificant on long term connectedness of DeFi and Islamic assets. Model 9 in Table 9 also exhibit captures a bit different impact as OVX become insignificant on long term connectedness and GFS exhibiting it negative influences. Model 9 captures 49.34% of variation in long term connectedness.

In summary, as observed in model 9, we noted that EPU has consistent negative impact of all frequency connectedness. VIX has a positive impact on total, short-term, medium-term, and long-term connectedness. OVX has negative on total and short-term connectedness but no significant impact on medium-term, and long-term. GVZ has insignificant impacts total and short-term, but it has negative on medium connectedness and long-term. GFS exhibit positive impact on total, short-term, and medium-term but negative impact for long-term connectedness. EVZ and CMLT exhibit consistently positive impact on across total, short, medium and long-term connectedness. EMV has positive on medium connectedness and long-term, but insignificant impacts total short-term. These findings confirm that global risk factors influence tail risk spillover between DeFi and Islamic assets and they can be determinants of spillovers. These findings are also supported by several past studies who found that global uncertainty factors and market uncertainty factors impact spillover (see, Billah et al., 2023; Billah et al., 2024; Elsayed et al., 2024; Hoque et al., 2023; Hoque et al., 2024).

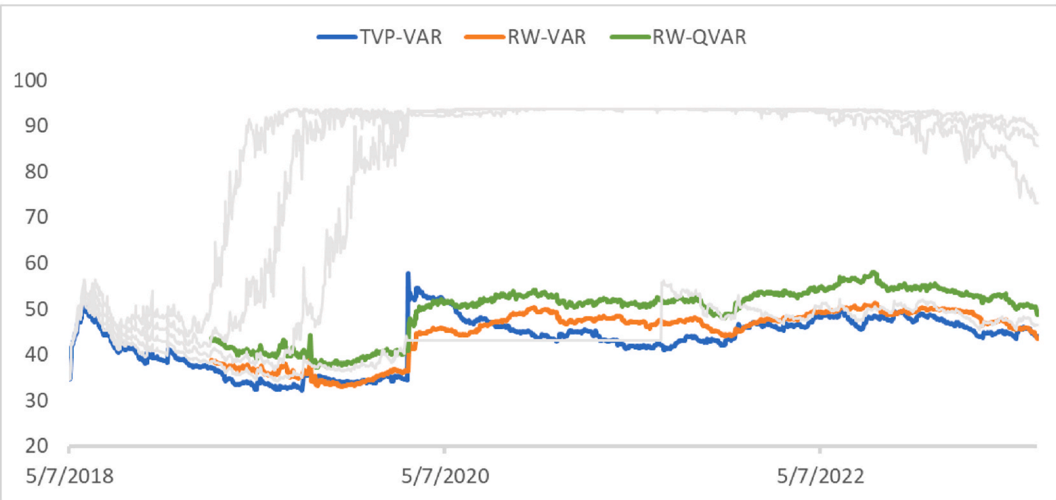
4.6. Results of the multivariate portfolio analysis

In this section, our focus shifts towards exploring the implications for portfolio diversification and risk hedging, employing the Minimum Connectedness Portfolio (MCoP) strategy aimed at minimizing pairwise interconnections across markets. Our investigation

Panel A: Forecast Horizon Sensitivity Analysis



Panel B: Decay Factor Sensitivity Analysis



Note: Panel A: Different forecast horizons are used [5, 15, 25, 35, 45].

Panel B: κ_1 = [0.95,0.96, 0.97, 0.98, 0.99] and κ_2 = 0.99

Fig. 5. Sensitivity analyses. Note: Panel A: Different forecast horizons are used [5, 15, 25, 35, 45]. Panel B: $\kappa_1 = [0.95, 0.96, 0.97, 0.98, 0.99]$ and $\kappa_2 = 0.99$.

focuses on evaluating both the hedging effectiveness (HE) and Sharpe ratios, which shed light on risk mitigation and profitability considerations across the various utilized indices. The outcomes of our analysis are presented in Table 10, segmented across distinct temporal periods: the full-sample duration (Panel A), the Covid-19 pandemic phase (Panel B), and the era of the Russian – Ukrainian war (Panel C).

Initiating our examination with average portfolio allocations during the full-sample period (Panel A), we observe that DeFi assets tend to occupy a range of 4%–7% in mean portfolio weights, collectively constituting an average weight of 24%. In contrast, average portfolio weights for Islamic assets usually span from 3% to 8%, with DJIM capturing the highest weight at 21%. This culminates in Islamic stocks and bonds holding an overall time-averaged weight of 77%. Amid the Covid-19 pandemic (Panel B), the time-averaged combined weight sees Islamic assets at 81%, with DeFis at 19%. Analogously, during the war phase (Panel C), Islamic and DeFi assets maintain a combined time-averaged weight of around 80% and 20%, respectively. These proportions closely mirror the 81% allocation for Islamic and 19% for DeFi assets witnessed during the Covid-19 period. It's worth noting that certain sukuks, namely Malaysian and Indonesian, exhibit a mean weight of 8% in both full and sub-samples, while DJSI maintains an average weight of 4%. Our findings imply that the inclusion of all these used assets from multivariate portfolios could provide advantageous outcomes for investors.

Table 6
Determinants of dynamic total tail risk spillovers for Defi assets, sukuk, and Islamic equity markets.

Coefficient	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
EPU	−0.025***								−0.013***
	(0.001)								(0.002)
VIX		0.230***							0.123***
		(0.023)							(0.043)
OVX			0.045***						−0.032***
			(0.008)						(0.011)
GVZ				0.507***					−0.036
				(0.038)					(0.066)
EVZ					0.848***				0.241***
					(0.088)				(0.127)
GFS						0.673***			0.568***
						(0.081)			(0.141)
EMV							−0.156***		0.017
							(0.015)		(0.015)
CLMT								0.012***	0.011***
								(0.001)	(0.001)
R^2(%)	23.34	30.20	29.00	30.3	28.07	29.80	28.00	20.00	55.59
N	1346	1346	1346	1346	1346	1346	1346	1346	1346

Note: Standard errors are printed in parenthesis. *, ** and *** show that the relevant coefficient is significant at the 10%, 5% and 1% level respectively. the dependent variable *TSI* (τ) is defined as total, short, medium, and long-term tail risk spillovers. Moreover, the term X_{it} contains the drivers of connectedness including the MSCI World Climate Change Index (CLMT), Equity Market Volatility (EMV), Economic Policy Uncertainty (EPU), Global Macroeconomic News Surprises (GMNS), Gold Market Volatility (GVZ), Global Financial Stress Index (GFS), Crude Oil Volatility (OVX), Real-time Market Index (VIX), and Equity Market Volatility (EMV). Table A2 presents the correlation matrix of the uncertainty variables and shows that there is no multicollinearity between these variables. Hence, Model 8 considers all explanatory variables at the same time.

Table 7
Determinants of dynamic Short – Term (1–5 days) tail risk spillovers for Defi assets, sukuk, and Islamic equity markets.

Coefficient	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
EPU	−0.020***								−0.010***
	0.001								(0.001)
VIX		0.205***							0.076***
		0.017							(0.030)
OVX			0.042***						−0.030***
			0.006						(0.008)
GVZ				0.444***					0.018
				0.028					(0.047)
EVZ					0.771***				0.122
					0.066				(0.091)
GFS						0.661***			0.657***
						0.061			(0.101)
EMV							−0.133***		0.005
							0.011		(0.011)
CLMT								0.010***	0.008***
								0.001	(0.001)
R^2(%)	33.34	24.20	31.00	32.3	26.07	31.80	29.00	33.00	47.77
N	1346	1346	1346	1346	1346	1346	1346	1346	1346

Note: Standard errors are printed in parenthesis. *, ** and *** show that the relevant coefficient is significant at the 10%, 5% and 1% level respectively. the dependent variable *TSI* (τ) is defined as total, short, medium, and long-term tail risk spillovers. Moreover, the term X_{it} contains the drivers of connectedness including the MSCI World Climate Change Index (CLMT), Equity Market Volatility (EMV), Economic Policy Uncertainty (EPU), Global Macroeconomic News Surprises (GMNS), Gold Market Volatility (GVZ), Global Financial Stress Index (GFS), Crude Oil Volatility (OVX), Real-time Market Index (VIX), and Equity Market Volatility (EMV). Table A2 presents the correlation matrix of the uncertainty variables and shows that there is no multicollinearity between these variables. Hence, Model 8 considers all explanatory variables at the same time.

Particularly striking is the dominance of DJIM, which consistently claims the largest single weight among all markets in the three sample periods, underscoring its pivotal role in a fixed-income investment portfolio.

Turning our attention to hedge effectiveness scores (HE), the full-sample results unveil a significant capacity for an investor to substantially diminish the volatility of individual assets within their portfolio, with reductions exceeding 75% for all DeFi markets based on mean portfolio weights. For instance, an investor allocating 4% of their portfolio to LINK could curtail portfolio risk by 77%. In contrast, with the exception of Sukuk Indonesia, all used Islamic stocks and bonds exhibit negative HE scores suggesting heightened

Table 8
Determinants of dynamic Medium – Term (5–22 days) tail risk spillovers for Defi assets, sukuk, and Islamic equity markets.

Coefficient	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
EPU	−0.004***								−0.002***
	(0.001)								(0.001)
VIX		0.023***							0.035***
		(0.005)							(0.010)
OVX			0.003***						−0.002
			(0.002)						(0.003)
GVZ				0.057***					−0.030**
				(0.008)					(0.016)
EVZ					0.061***				0.058**
					(0.019)				(0.030)
GFS						0.024			−0.036
						(0.017)			(0.034)
EMV							−0.019***		0.007**
							(0.003)		(0.004)
CLMT								0.002***	0.002***
								(0.001)	(0.001)
R^2(%)	13.34	24.20	21.00	31.3	25.07	27.80	25.00	18.00	57.45
N	1346	1346	1346	1346	1346	1346	1346	1346	1346

Note: Standard errors are printed in parenthesis. *, ** and *** show that the relevant coefficient is significant at the 10%, 5% and 1% level respectively. the dependent variable *TSI* (τ) is defined as total, short, medium, and long-term tail risk spillovers. Moreover, the term X_{it} contains the drivers of connectedness including the MSCI World Climate Change Index (CLMT), Equity Market Volatility (EMV), Economic Policy Uncertainty (EPU), Global Macroeconomic News Surprises (GMNS), Gold Market Volatility (GVZ), Global Financial Stress Index (GFS), Crude Oil Volatility (OVX), Real-time Market Index (VIX), and Equity Market Volatility (EMV). Table A2 presents the correlation matrix of the uncertainty variables and shows that there is no multicollinearity between these variables. Hence, Model 8 considers all explanatory variables at the same time.

Table 9
Determinants of dynamic Long – Term (more than 22 days) tail risk spillovers for Defi assets, sukuk, and Islamic equity markets.

Coefficient	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
EPU	−0.003***								−0.001***
	(0.001)								(0.001)
VIX		0.002							0.013***
		(0.002)							(0.005)
OVX			−0.001						0.003
			(0.001)						(0.001)
GVZ				0.006***					−0.025***
				(0.004)					(0.007)
EVZ					0.015***				0.061***
					(0.008)				(0.014)
GFS						−0.011			−0.053***
						(0.007)			(0.015)
EMV							−0.005***		0.004***
							(0.001)		(0.002)
CLMT								0.002***	0.002***
								(0.001)	(0.001)
R^2(%)	33.34	24.24	31.10	21.30	22.07	19.80	21.45	26.33	49.34
N	1346	1346	1346	1346	1346	1346	1346	1346	1346

Note: Standard errors are printed in parenthesis. *, ** and *** show that the relevant coefficient is significant at the 10%, 5% and 1% level respectively. the dependent variable *TSI* (τ) is defined as total, short, medium, and long-term tail risk spillovers. Moreover, the term X_{it} contains the drivers of connectedness including the MSCI World Climate Change Index (CLMT), Equity Market Volatility (EMV), Economic Policy Uncertainty (EPU), Global Macroeconomic News Surprises (GMNS), Gold Market Volatility (GVZ), Global Financial Stress Index (GFS), Crude Oil Volatility (OVX), Real-time Market Index (VIX), and Equity Market Volatility (EMV). Table A2 presents the correlation matrix of the uncertainty variables and shows that there is no multicollinearity between these variables. Hence, Model 8 considers all explanatory variables at the same time.

portfolio volatility during the full sample period. These findings persist across various market scenarios, such as the Covid-19 and the war periods (Panels B and C). Exceptionally, these two, periods saw DJIUS with a positive HE scores, suggesting reduced portfolio volatility. The hedging effectiveness of DeFi assets appears even more pronounced during the war and Covid-19 phases (with values higher than 91%), indicating their stability as risk reduction assets. Meanwhile, Islamic indices consistently fail to demonstrate meaningful hedging potential across all examined periods. In essence, these findings lend credence to the notion of compelling diversification prospects among the studied markets.

Table 10
Dynamic multivariate portfolio weights Minimum Connectedness Portfolio (MCoP) based on TVP-VAR model.

Panel A: FULL SAMPLE							
	MEAN	STD.D	5%	95%	HE	P-VALUE	SHARPE RATIO
DJIEM	0.06	0.08	0.00	0.23	−5.40	0.00	−0.218
DJIM	0.21	0.16	0.00	0.44	−5.32	0.00	2.985
DJIE	0.03	0.07	0.00	0.21	−4.87	0.00	1.515
DJIA	0.04	0.08	0.00	0.22	−6.77	0.00	0.072
DJIGCC	0.03	0.04	0.00	0.11	−9.09	0.00	2.572
DJIUS	0.05	0.08	0.00	0.23	−3.09	0.00	3.378
DJIUK	0.07	0.07	0.00	0.21	−4.33	0.00	0.654
DJSI	0.04	0.06	0.00	0.16	−377.71	0.00	7.304
Sukuk Malaysia	0.08	0.07	0.00	0.20	−395.20	0.00	12.365
Sukuk Indonesia	0.08	0.06	0.00	0.18	0.98	0.00	−0.218
Sukuk GCC	0.08	0.09	0.00	0.24	−368.22	0.00	6.920
LINK	0.04	0.05	0.00	0.15	0.77	0.00	4.139
MKR	0.05	0.04	0.00	0.14	0.80	0.00	3.898
BAT	0.04	0.04	0.00	0.12	0.77	0.00	2.894
SNX	0.07	0.06	0.00	0.18	0.75	0.00	−0.002
BNT	0.04	0.04	0.00	0.13	0.77	0.00	3.178

Panel B: COVID-19	***MEAN***	***STD.D***	***5%***	***95%***	***HE***	***P-VALUE***	***SHARPE RATIO***
DJIEM	0.07	0.04	0.00	0.15	−0.58	0.00	3.385
DJIM	0.36	0.15	0.00	0.48	−0.46	0.00	5.856
DJIE	0.02	0.06	0.00	0.18	−0.55	0.00	3.990
DJIA	0.02	0.06	0.00	0.19	−1.14	0.00	4.036
DJIGCC	0.04	0.03	0.00	0.06	−1.06	0.00	5.060
DJIUS	0.02	0.06	0.00	0.17	0.07	0.43	5.694
DJIUK	0.04	0.05	0.00	0.16	−0.20	0.03	1.282
DJSI	0.04	0.06	0.00	0.20	−107.38	0.00	10.346
Sukuk Malaysia	0.08	0.04	0.00	0.14	−77.88	0.00	6.185
Sukuk Indonesia	0.08	0.04	0.00	0.10	0.94	0.00	−4.091
Sukuk GCC	0.04	0.04	0.00	0.12	−110.84	0.00	9.947
LINK	0.03	0.03	0.00	0.09	0.95	0.00	2.758
MKR	0.05	0.02	0.00	0.08	0.95	0.00	5.136
BAT	0.05	0.02	0.02	0.07	0.95	0.00	5.167
SNX	0.05	0.03	0.01	0.10	0.95	0.00	−1.726
BNT	0.02	0.03	0.00	0.07	0.91	0.00	2.772

Panel C: Russia – Ukraine WAR	***MEAN***	***STD.D***	***5%***	***95%***	***HE***	***P-VALUE***	***SHARPE RATIO***
DJIEM	0.07	0.04	0.00	0.15	−0.58	0.00	−6.049
DJIM	0.36	0.15	0.00	0.48	−0.46	0.00	−0.629
DJIE	0.02	0.06	0.00	0.18	−0.55	0.00	−1.702
DJIA	0.02	0.06	0.00	0.19	−1.14	0.00	−4.614
DJIGCC	0.04	0.03	0.00	0.06	−1.06	0.00	−2.505
DJIUS	0.02	0.06	0.00	0.17	0.07	0.43	0.443
DJIUK	0.04	0.05	0.00	0.16	−0.20	0.03	−1.726
DJSI	0.04	0.06	0.00	0.20	−107.38	0.00	−7.240
Sukuk Malaysia	0.08	0.04	0.00	0.14	−77.88	0.00	10.413
Sukuk Indonesia	0.08	0.04	0.00	0.10	0.94	0.00	0.585
Sukuk GCC	0.04	0.04	0.00	0.12	−110.84	0.00	−6.493
LINK	0.03	0.03	0.00	0.09	0.95	0.00	2.033
MKR	0.05	0.02	0.00	0.08	0.95	0.00	2.837
BAT	0.05	0.02	0.02	0.07	0.95	0.00	−1.811
SNX	0.05	0.03	0.01	0.10	0.95	0.00	1.604
BNT	0.02	0.03	0.00	0.07	0.91	0.00	0.388

Notes: This table illustrate the hedge ratios, between Defi assets, sukuk and Islamic equity markets in full sample, Covid-19 and Russia – Ukraine WAR.

Lastly, delving into Sharpe ratios, it becomes evident that most DeFi assets, with the exception of SNX, exhibit strong performance during the full-sample period. LINK exhibits the highest Sharpe ratio of 4.139, while MKR and BNT impressively combine risk reduction with diversification, boasting a HE of 80% and 77% and Sharpe ratios of 3.898 and 3.178, respectively. Within the realm of Islamic assets, Sukuk Malaysia leads the pack with a Sharpe ratio of 12.365. The majority of Islamic stocks and bonds showcase positive risk-adjusted performances, except for DJIEM and Sukuk Indonesia during the full sample. As we enter the Covid-19 period (Panel B), the majority of DeFi and Islamic assets, with the exceptions of SNX and Sukuk Indonesia, consistently exhibit positive Sharpe ratios. This trend suggests that the inclusion of these assets in a portfolio is poised to yield notably higher returns and/or lower risks. However, transitioning to the RU war period, a broader array of Islamic indices displays negative Sharpe ratios. Notably, Malaysian and Indonesian sukuk markets surface as the top performers during this period, with Sharpe ratios of 10.413 and 0.585, respectively.

4.7. Policy implications and discussion

The study's findings offer significant insights for investors looking to diversify their portfolios and hedge against risks. The moderately weak integration between DeFi assets and Islamic assets presents an opportunity for investors to achieve better diversification. For instance, the persistent connection between SNX (a DeFi token) and sukuk markets suggests that SNX can be a valuable asset in diversifying risk in Islamic fixed-income portfolios. This connection is particularly notable for medium- and long-term horizons, indicating its potential as a long-term investment. An investor holding a portfolio of traditional Islamic financial instruments, such as sukuks and Islamic equities, can enhance diversification by including DeFi assets like SNX. During the COVID-19 pandemic, the study found that DeFi and Islamic assets exhibited moderate spillover effects, which means they did not move in tandem. This non-correlation implies that adding DeFi assets to a traditional Islamic portfolio can reduce overall portfolio risk and improve risk-adjusted returns. Investors can also use DeFi assets as a hedge against market volatility. For example, during the initial phase of the COVID-19 pandemic, the study observed elevated spillover effects. By strategically including DeFi assets in their portfolios, investors can mitigate the impact of market shocks. The findings show that DeFi indices play a significant role in fixed-income portfolios, with associated weights ranging from 19% to 24%, and consistently demonstrating high hedging effectiveness of more than 75%. This means that in times of market stress, DeFi assets can act as a buffer, protecting the portfolio from significant losses. For example, an investment fund could create a balanced portfolio that includes 50% traditional Islamic assets (sukuks and equities) and 50% DeFi assets. The study shows that such a portfolio would benefit from the weak integration between the two asset classes, providing a hedge against market volatility. For instance, during market downturns triggered by geopolitical events, the DeFi assets could help stabilize the portfolio's performance.

The findings suggest that DeFi and Islamic finance markets exhibit distinct behaviors, especially under extreme market conditions. Policymakers need to design regulatory frameworks that take into account these unique characteristics to ensure financial stability. Understanding the tail risk connectedness between these markets can help policymakers in developing regulations that mitigate systemic risks. During the Russian-Ukrainian conflict, the study found that the connectedness between DeFi and Islamic assets was more pronounced across all time horizons. Policymakers can use these insights to formulate policies that provide additional safeguards for financial markets during geopolitical tensions. For instance, implementing stress tests that consider the unique spillover dynamics of DeFi and Islamic assets can help regulators anticipate and mitigate potential risks. For example, testing the resilience of financial institutions to shocks in DeFi markets and their subsequent impact on Islamic financial assets during crises like the COVID-19 pandemic and the Russia-Ukraine war.

Policymakers must strike a balance between encouraging financial innovation and ensuring market stability. The study's findings on the hedging capabilities of DeFi assets highlight their potential to contribute to a more resilient financial system. Regulations that support the growth of DeFi while implementing measures to manage associated risks can foster a more robust financial ecosystem. Market participants, including financial institutions and asset managers, can leverage the study's insights to better manage risks and optimize their investment strategies. The time-varying connectedness observed during the COVID-19 pandemic and the Russia-Ukraine conflict suggests that market participants need to be aware of how global uncertainties affect different asset classes. Asset managers can use the findings to adjust their asset allocation strategies dynamically. For instance, during periods of high global uncertainty, such as the early stages of the COVID-19 pandemic, increasing the allocation to DeFi assets can provide a hedge against volatility in Islamic markets. Conversely, during more stable periods, the allocation can be adjusted to maximize returns from other asset classes. Financial institutions can develop new investment products that combine DeFi and Islamic assets to cater to investors seeking both diversification and compliance with Shariah principles. For example, a mutual fund that includes a mix of sukuks, Islamic equities, and select DeFi tokens could attract investors looking for innovative and diversified investment opportunities. They could develop hedging funds that specifically target the spillover effects identified in the study. For example, a hedging fund could hold significant positions in SNX and sukuks, exploiting the consistent connection between these assets for medium- and long-term risk management.

5. Conclusion

Investors and regulators are closely following decentralized finance (DeFi) as it has the potential to transform the traditional financial system. From an academic viewpoint, there is a limited body of financial literature, to date, that examines the opportunities, risks, and boarder ramifications of DeFi assets within the global financial landscape. In this study, we delve into the impact exerted by DeFi indices on Islamic stock and bond markets. Our analysis specifically focuses on the transmission of risks across DeFi assets, along with Islamic equities and bonds, thereby concentrating on the implications for portfolio management. To investigate this, we employ advanced econometric methodologies recently developed, leveraging daily data spanning from May 31, 2018 to July 07, 2023, and employ a time-frequency connectedness approach.

An examination of static directional spillovers reveals fluctuations in the average interconnections among DeFi assets, sukuk markets and Islamic equity indices, across short-, medium-, and long-term periods. Notably, our findings underscore that the spillover effects among these markets predominantly arise from short-term information, emphasizing the relevance of employing a time-specific analytical framework.

Our research identifies a moderately weak integration between DeFi, sukuks and Islamic stock markets. However, whilst all the other DeFi assets seem to be disconnected from both sukuks and Islamic stock markets at various time horizons, there seems to be a potent and persistent connection that emerges between SNX, within the DeFi domain, and sukuk markets, except Indonesian, spanning the medium- and long-term time horizons. Our interpretation of these results suggests that DeFi is still not a mature market, with indications that such an ecosystem might wield more substantial influence and financial integration in the future than they presently do.

Turning our focus to used DeFi indices, our findings indicate that, while these indices are not significantly impacted by shocks originating from their peers in the short-term perspective, the backlinks become more substantiated, spanning the medium-, and long-term timeframes. This observation supports the notion that DeFi operates as self-sufficient ecosystem, capable of influencing Islamic bonds while remaining relatively independent of the developments in other markets.

Through an analysis of time-varying connectedness, we observe an elevation in spillover effects during the initial phase of the COVID-19 pandemic, across all time scales. Nevertheless, these effects are moderate, especially for medium- and long-time intervals, suggesting the potential existence of substantial diversification advantages and a hedging effect of these assets.

Examining the COVID-19 era and the period of the Russian-Ukrainian conflict, our results highlight more established connections between DeFi and Islamic sukuks and equities across medium and long terms for the Covid-19 period, and across all time horizons, when considering the period of the Russian-Ukrainian war. Nonetheless, a stable disconnection between BNT and all the Islamic indices, across all timeframes is also noticed. Additionally, apart from the discernible albeit somewhat modest link established between LINK and DJIGCC at the long-term horizon, the linkages between Defi and Islamic indices display a tendency to wane during the war period in the long-term. Notably, beyond the specific market interconnections, the insights from our analysis suggest potential diversification benefits associated with holding portfolios consisting of these two assets.

In the final stage of our analysis, we leverage the estimated time-varying variance-covariance matrix to derive insightful portfolio implications using the minimum connectedness portfolio (MCoP) construction technique. Our results indicate a significant role for DeFi indices within fixed-income portfolios encompassing both Islamic stocks and sukuks. Specifically, our findings reveal a noteworthy economic role played by these indices, with associated weights ranging from 19% to 24%, while consistently demonstrating high scores of hedging effectiveness of more than 75%.

This study bears essential implications for various stakeholders, including investors, regulatory bodies, and policymakers. For Islamic investors, our findings underscore the potential to enhance portfolio performance through investment in DeFi assets. Furthermore, we shed light on the co-evolution and interactions between DeFi and Islamic stocks and bonds, thereby offering valuable insights for regulatory and policy evaluation within the context of this new decentralized ecosystem. Moreover, ethical, and more particularly, Islamic companies can glean insights into their relationships with decentralized finance, thereby facilitating strategic decisions aligned with the evolving landscape.

One significant limitation of our study is data constraint. Our study focuses on a specific subset of DeFi indices, sukuks, and Islamic equity indices. This selection, while comprehensive, does not encompass the entire spectrum of DeFi and Islamic financial instruments. Other emerging DeFi assets and broader Islamic financial products might exhibit different spillover and connectedness patterns. Another limitation is that the DeFi market is still in its nascent stages, and our findings suggest it is not yet fully mature. The behaviors and interconnections observed might change as the market matures and as regulatory frameworks evolve. Future research could extend the data period to include more recent developments in DeFi and Islamic finance. Expanding the scope to include a wider range of DeFi and Islamic financial instruments could offer deeper insights. Future studies might consider additional DeFi assets, such as decentralized insurance tokens or more diverse Islamic financial products, including waqf and takaful. Conducting sector-specific analyses within DeFi and Islamic finance could uncover unique patterns of connectedness. For example, examining the impact of DeFi lending platforms on Islamic microfinance institutions could provide targeted insights.

Table A.1
Variables to Determine the Spillovers

Variable	Description
EPU	The EPU index assesses the coherence of domestic newspaper data in terms of three factors: the economy (E), policy (P), and uncertainty (U). Previous studies have found a negative link between changes in EPU and various financial market returns (Balli et al., 2020), so we can anticipate a negative sign from EPU.
VIX	The VIX is a crucial market index that accurately reflects real-time volatility and predicts the upcoming 30-day volatility. It's imperative to note that any increase in the VIX has a negative impact on Islamic banks and Fintech markets, leading to a significant decrease in TSI. Hence, we anticipate a negative indication for the VIX and urge you to take necessary precautions.
OVX	The estimated 30-day volatility of crude oil, known as OVX, is determined by the pricing set by the US Oil Fund (USO). An increase in the OVX is associated with a negative impact on the stock market prices, as noted by Saeed et al. (2021), leading to a decrease in the TSI. Thus, we can anticipate a negative indication from OVX.
GVZ	The GVZ, also known as the Gold Volatility Index, is a tool that offers an approximation of the anticipated level of volatility in the returns of the SPDR Gold Shares ETF (GLD) within a 30-day timeframe.
GFS	Bank of America Merrill Lynch utilizes the Global Financial Stress Index to predict cross-market risk, demand protection, and financial investment flows in the worldwide financial process.
EVZ	The volatility of the euro/U.S. dollar exchange rate can be tracked using the CBOE Euro Currency Volatility Index which estimates the market's projection of 30-day volatility by using the VIX technique on options for the Currency Shares Euro Trust (FXE).
EMV	According to Baker et al. (2019), the Equity Market Volatility (EMV) tracker is an index based on eleven major U.S. newspapers. This index is highly correlated with the VIX and with realized volatility on the S&P 500.

(continued on next page)

Table A.1 (*continued*)

Variable	Description
CLMT	The MSCI World Climate Change Index (CLMT) is a critical index that encompasses significant and mid-cap securities across 23 Developed regions. It is linked to the MSCI World Index and aims to showcase the effectiveness of an investment strategy by re-weighting securities based on opportunities and risks associated with the transition to a lower carbon economy. The index also strives to eliminate exemptions from the relative index.

Table A.2
Correlation Coefficients of Explanatory Variables

Explanatory variables	EPU	VIX	OVX	GVZ	GFS	EVZ	EMV	CLMT
EPU	1.00							
VIX	0.15	1.00						
OVX	0.18	0.33	1.00					
GVZ	0.13	0.31	0.16	1.00				
GFS	−0.20	0.17	0.24	0.19	1.00			
EVZ	0.19	−0.17	0.28	−0.22	−0.18	1.00		
EMV	0.23	0.19	−0.10	0.11	−0.24	0.17	1.00	
CLMT	0.10	0.29	0.35	0.33	0.23	−0.09	−0.20	1.00

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.

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